Managerial Turnover, Fund Family Tournament and Investors Learning in the UK Fund Market

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To my parents

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ABSTRACT

This research is constructed to provide a comprehensive analysis of key factors that influence fund performance, and the methods of evaluating such performance. Our examination is from both the managerial and the investor perspectives in the context of the UK fund industry.

We begin by analysing the managerial response. We examine the effectiveness of the internal monitoring and control system in UK funds, focusing on the relation between top manager turnover and the performance of UK unit trusts and OEICs. We apply a series of methods, including performance evaluation based on the factor models, percentile ranking, and sample matching tests. Funds that have experienced replacement of top managers are examined for their performance in the pre and post-replacement periods. A variety of methods are applied to measure factors that affect the probability of replacement in the pre-replacement period. Bootstrapping simulations are implemented to further examine whether UK fund companies can distinguish between poorly skilled managers and unlucky ones. It is found that many fund companies are not captivated by the 'lucky' managers' extreme performance and are willing to give 'unlucky' managers another chance. Moreover, underperforming managers are more likely to be replaced when fund inflows are declining than are outperforming managers. Managers' adjustment of portfolio compositions exerts mixed influences on the probability of replacement.

Next, we apply tournament analysis to the UK fund market. We find supportive

evidence of significant risk shifting in the family tournament; i.e. interim winning managers tend to increase their levels of risk exposure more than the losing managers do. Our results also show that the risk-adjusted returns of the winners outperform those of the losers following the risk taking. As such, risk altering can be regarded as an indication of managers' superior ability. However, the tournament behaviour can still be a costly strategy for investors, since in this case winners would be seen as beating the losers in terms of the observed returns due to deterioration in the performance of their major portfolio holdings.

Finally, the thesis further examines the cross-fund learning among investors. A linear hierarchical model is constructed to consider cross-learning of the funds within a fund family in performance evaluation. We apply a full Bayesian treatment of all factors of the pricing model and allow both the fund family and individual managers to have dependent prior information regarding the funds' alphas. The simulation results suggest that returns from peer funds within the family significantly affect investors' updating on fund alphas, since the posterior distribution on fund alphas exhibits a faster shrinkage than is reported in the previous literature. The model is also simulated with various prior beliefs on different factors of the pricing model, i.e. fund alphas, betas and factor loadings of each pricing benchmark, to better address the learning process.

DECLARATION

No part of this thesis has been submitted elsewhere for any other degree or qualification in this or any other university. It is all my own work unless referenced to the contrary in the text.

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CHAPTER ONE

INTRODUCTION

1.1 The objective of the thesis

This research aims to provide a comprehensive analysis of key factors that influence the mutual fund performance, and the technique for performance evaluation. Our examination is from both the managerial and the investor perspectives in the context of the UK fund industry. We begin by examining the effectiveness of the internal monitoring and control system which affect funds' risk-adjusted performance. Then we apply the tournament analysis to provide insight into the interplay between fund managers' risk shifting and performance changing. Finally, the research is further extended to construct performance evaluation method which consider the cross-learning of the information given by funds within a fund family. The specific objectives of each chapter are addressed by the following points.

In Chapter 2 where the effectiveness of the internal monitoring and control system in the UK fund industry is discussed, our research aims to,

1. Shed critical light on the effectiveness of the internal monitoring and

control system by analysing the relation between top manager turnover and the performance of UK unit trusts.

2. To provide further insight into the performance contribution of the fund managers around replacement, a simulation procedure is implemented to test whether, in their managerial dismissal and appointment, UK fund companies can distinguish between managers with genuine skills and those who are lucky, or between poorly skilled managers and those who are unlucky.

3. In order to comprehend the trading and investment behaviour from both the investors and the managers around the replacement, this chapter also provides additional test regarding the changes of capital inflow and portfolio characteristics. We compare funds' top holdings, equity holdings and industry concentration before and after the top management turnover while the flow changes is examined by the size shifting around the replacement.

In Chapter 3 where mangers' risk taking and performance consequences is examined,

1. To analyse the distinct risk taking behaviour between interim winning and losing managers, we construct empirical models in the context of the

segment and family tournament in which managers within the same segment (family) might compete with each other by increasing the portfolio risk to improve future performance.

2. To reveal the connection between the risk taking and managers' career concern, we further examine managers' risk taking behaviour under different market condition, namely, how mid-year winners (losers) adjust their risk level during the bull market when compensation overwhelms employment concern or vice versa in the bear market.

3. We conduct the performance consequence analysis for both the interim winners and losers to examine the costs and gains for the risk shifting. We compute the difference of raw returns as well as the risk adjusted returns with respect to funds' changes in total risks. We also look into the risk shifting issue from the overall family perspective by comparing the aggregated performance shifting between the dog family (family consists of funds whose performance is extremely poor) and star family (family consists super star funds). Our analysis therefore shed the additional light on managers' motivations and families' view regarding the risk taking.

In Chapter 4, the objectives of the chapter can be stated as following,

1. To incorporate the return information given by peer funds within the same

fund family, we construct a linear hierarchical model to provide alternative performance evaluation results. The dependent nature of the variability of funds' alphas can be modelled in a hierarchical setting in which a dependent prior is designated on the cross-sectional mean. The alpha of a fund can be drawn from a common population distribution which is defined to describe the general belief on the cross-sectional performance. A prior can then be assigned to represent the investors' opinion on the mean of the distribution, since its posterior mean is the weighted average of the information from both the prior and the data.

2. In order to utilize the return information from the other pricing factors given by the peer funds, we apply a separation strategy suggested by several statistical studies to decompose the covariance matrix into the production of the diagonal matrix with variance of each factor, and the correlation matrix of all the factors in the pricing model. By deploying the separation strategy we can define the prior information on each of the pricing factors as well as the between-factor correlation. The full Bayesian treatment on each of the variable considered in the pricing model in addition to the alpha, i.e. the systematic risk; the factor loadings on the size, book to market and the momentum portfolio can better address the learning behaviour. By including information given by all pricing factors

we manage to find out that from the investors' perspective how beliefs on other issue from the pricing model affect the updating of individual fund alpha. Moreover, we place no restriction on the correlation matrix of different pricing factors in the pricing model. That is to say we also include prior information to allow cross-factor learning which is often impossible in the conventional OLS estimated alphas.

1.2 An overview of the UK fund industry

The rapid expansion of the UK fund industry in recent years has pushed it from fifth place in the world league table of asset value ranks (Gremillion, 2005) to become the world's second largest after the US in terms of asset management activity. By the end of 2011, the UK's Unit Trusts and Open-end Investment Companies (OEICs hereafter),[1] which are mainly retail vehicles, were managing £575 billion worth of assets. Despite the fallout of the 'Dot-com' crash and the recent global financial crisis, during the period 2001 to 2011 the UK fund industry grew by almost 143% in asset value.[2]

Among all the types of assets under management by the UK fund industry,

[1] Unit trusts and OEICs are UK equivalents of US mutual funds. The key difference between unit trusts and OEICs is dual pricing, i.e. unit trusts have offer and bid prices while OEICs are singly priced at Net Asset Value (NAV).

[2] Data source: The Investment Management Association Annual Survey 2012.

equities account for the largest proportion. With £333 billion of equities under their management by 2011, over one quarter of the UK funds construct their portfolios primarily in equities, and over 50% of the investments are focused on UK stocks. According to the Investment Management Association (IMA), the UK All Companies and UK Equity Income are the two leading sectors of all fund sectors by asset value. The three purely UK-focused sectors, i.e. UK All Companies, UK Equity Income and UK Smaller Companies, contribute to an aggregate of £157 million in terms of assets under management, which is 47% of the overall asset value of all the equity sectors.[3] As such, the data sample built by the UK domicile equity funds is sufficiently representative of major characteristics of the UK equity funds.

A typical UK fund includes the trustees, the investment advisers, unit holders and management companies. Figure 1.1 depicts the cash flow and major entities of the UK unit trusts industry. The investors provide the trusts with money when they purchase their shares. The trusts then use the money to construct portfolios in accordance with their investment objective. Investors receive money when they redeem shares from the trusts. The trustees are empowered with the overall control of the underlying assets and devote efforts to protect unit holders' interests. The management companies take responsibility for fund administration. They fire

[3] Other IMA equity sectors may also contain some UK-focused funds, but usually only in small numbers; for example, there may be Europe and UK specialist funds in Technology and Telecommunications, etc.

or hire fund managers according to the decision of trustees based on financial advisers' advice on managerial replacement. Assuming this mechanism is efficient, performance of a fund manager is negatively associated with the probability of dismissal.

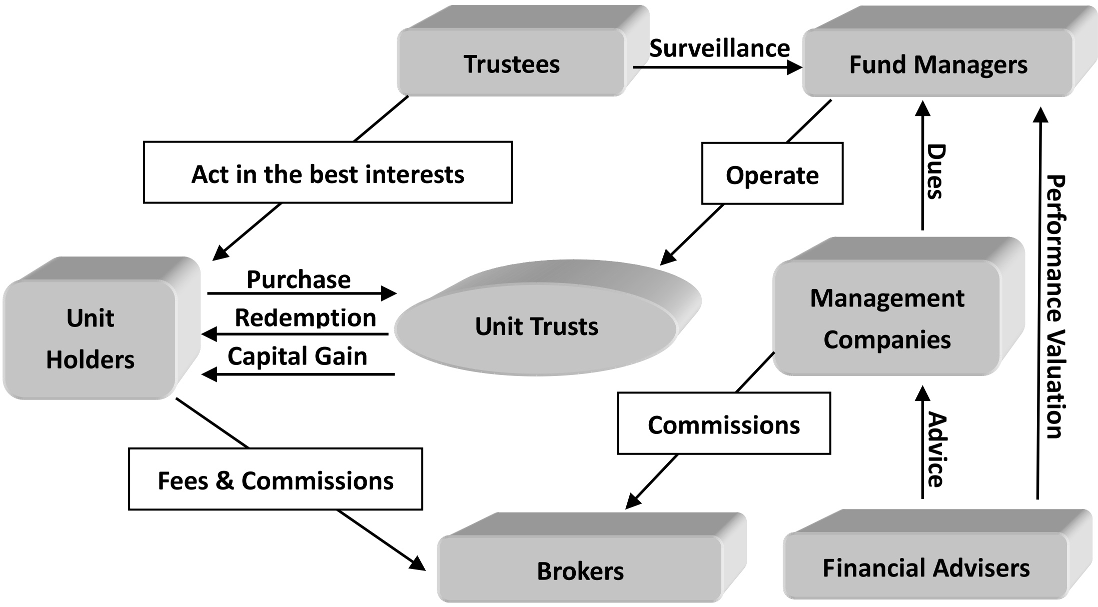


Figure 1.1 Cash Flow and Major Entities in the UK Unit Trusts Industry

The role of fund directors (or the trustees of unit trusts) is different from that of the board of directors, since the latter's major responsibility is internal monitoring. In the fund industry, fund directors are the fiduciaries that should act in the best interests of the fund holders. However, their powers in that respect are diluted, since fund companies have developed a close connection with the fund directors.

1.3 Fund performance evaluation

Existing research analyses evaluation of fund performance on the basis of two criteria: the observed returns and the risk-adjusted returns. The observed returns show a fund's delivered performance instantly. They are normally computed by the difference of the funds' NAV within a certain data frequency. Given the simplicity of this criterion, the observed returns are widely used by most of the ranking agencies, e.g. Morningstar and Trustnet. In academic research, Chevalier and Ellison (1997) and Sirri and Tufano (1998) for example examine changes of cash flow in response to observed returns. While Brown, Harlow and Starks (1996), Kempf and Ruenzi (2008), and Schwarz (2012) analyse the changes of risk with respect to the average of half-year observed returns, Patel, Zeckhauser and Hendricks (1994) argue that investors might value observed returns more than the risk-adjusted returns.

The risk-adjusted returns, also known as the Jensen alpha, are widely used as the criterion for judging managers' stock selection ability. Jensen (1968) divides the economic contents of portfolio performance into two components, the ability of the portfolio manager and the ability to minimize the insurable risk. Based on this division he proposes a measurement to evaluate the performance of the portfolio, the difference between the actual and normal risk premium based on capital asset pricing model, and it is known as the Jensen alpha. In Fama and French (1993) and Carhart (1997), Jensen's basic framework is extended to include portfolio size, book-to-market ratio and momentum effects in mimicking the investment strategies. Subsequently, the effectiveness of alpha as the criterion for judging managers' stock selection skills has been widely reviewed, and a variety of methodologies has been adopted in the estimation of alpha (Lehman and Modest, 1987; Grinblatt and Titman, 1989, 1993; Goetzmann and Ibbotson, 1994; Malkiel, 1995, and Wermers, 2000). Meanwhile, several studies have considered precise estimation of alphas, for example the seemingly unrelated model by Pastor and Stambaugh (2002), the liquidity model by Pastor and Stambaugh (2003) and the time varying model by Ferson and Schadt (1996).

Despite the considerable efforts made in the previous research to construct an appropriate pricing model in order to gain more precise evaluation results, few studies have realised that the risk-adjusted returns are also hampered by the magnificent randomness in the market (Pastor and Veronesi, 2009). Alphas given by the frequentist estimation cannot address the randomness issue, while a Bayesian updating may instead rationalise the investors' beliefs after receiving new information, and better address the uncertainty in financial data.

The Bayesian process can be regarded as a combined estimation of both prior beliefs and the observed data. The prior belief about an uncertain parameter is elicited before seeing the actual data used to estimate that parameter. For instance, from the fund investors' perspective, the frequentist approach is to compute the fund alpha directly by using the observed returns within a certain pricing model. However, in the Bayesian approach, investors also receive additional information related to the alpha they aim to compute, i.e. the opinion on the manager's ability based on past experience, and the historical returns which can be used to price the market benchmark in a certain pricing model. Investors can incorporate the prior beliefs in the estimation to generate the posterior distribution. The posterior mean can also be used as new prior information in future updating.

Given the interest in such a rational updating process, some researchers have chosen to conduct the evaluation process using the Bayesian approach. Kandel, McCulloch and Stambaugh (1995), and Pastor and Stambaugh (2000) discuss this from the portfolio selection perspective. Baks et al. (2001) consider various elicitations of investors' prior beliefs in asset allocation. Pastor and Stambaugh (2002), and Busse and Irvine (2006) manage to incorporate information given by the non-included benchmark portfolio in the pricing model to compute the funds' alphas, in which a seemingly unrelated model is constructed in a Bayesian framework.

Past research related to the Bayesian evaluation of funds' performance is mainly constructed with independent prior beliefs which ignore the dependent nature of the cross-sectional variability in fund alphas, as if the stock selection ability of the manager could only be identified through a certain sample of his past observed returns. Thus, the randomness in the historical returns might hamper the conventional method from addressing the manager's true ability. Jones and Shanken (2005) therefore consider a dependent prior belief to incorporate the cross-sectional mean and standard deviation of fund alphas in the Bayesian updating. They find that investors with high scepticism of cross-sectional managers' skills are more convinced of the inferior ability of the funds they hold. They argue that this outcome is due to cross-fund learning at the investors' end. Consequently, dependent prior belief facilitates Bayesian updating to include additional information given by related parties, to better address the uncertainty of parameters in financial markets.

1.4 Performance shifting

1.4.1 Risk taking and performance shifting

Performance shifting is another popular area to which previous research devotes much attention. Changes in funds' performance may be due to a variety of factors, but all can be grouped into two categories: managerial issues and investment strategy related issues. Of these, risk taking proves to be a major channel for the performance changes, since it can exert a considerable effect on portfolio management.

Mutual funds change their risk exposure over time (Brown, Harlow and Starks, 1996; Kempf and Ruenzi, 2008; Huang, Sialm and Zhang, 2011). Many studies argue that this is primarily related to the agency problem. Previous literature finds a convex shaped relation between fund performance and changes in cash inflows (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Huang, Wei and Yan, 2007). Given this disproportionate flow-performance connection, underperforming managers may be tempted to increase risk exposure to bet on performance improvement, since the manager's compensation scheme is based on a fixed percentage rate over the underlying assets.

Studies such as Koski and Pontiff (1999), Elton, Gruber and Blake (2003), Qiu (2003) and Hu, Kale, Pagani and Subramanian (2011) find that risk altering is closely related to managers' implicit compensation. Underperforming funds may also alter levels of their portfolio risk before the reporting date to manipulate their performance record or to increase holdings of the equities with recent good performance to window dress the investments (Lakonishok, Shleifer, Thaler and Vishny, 1991; Goetzmann, Ingersoll, Spiegel and Welch, 2007). However, risk shifting is not necessarily accompanied by performance improvement. Using datasets based on portfolio holdings, Huang et al. (2011) suggest that funds with high levels of risk cannot outperform those with a stable level of risk. They claim that risk taking is merely an indication of managers' inferior skill, or is initialised by the agency issue.

1.4.2 Fund family and performance shifting

Several studies relate the performance of individual funds to the fund families to which they belong. Fund families play an important role in funds' operation, since it is the fund family that decides managers' promotion or demotion, and which funds to market (Jain and Wu, 2000). Gervais, Lynch and Musto (2005) find that fund companies might better convey the information on managers' skills to the investors. Khorana and Servaes (1999) document that large fund families are more likely to open new funds. Baks (2003) uses a Cobb-Douglas production function to identify the performance attribution of the fund family in individual funds' alphas.

Strategies adopted by fund companies can also affect the performance of individual funds. Massa (2003) finds that the fund family can adopt various strategies to attract investors, such as allowing investors to switch between funds within the same fund family or increasing product differentiation within the family, which in turn has an impact on individual fund performance. Gaspar, Massa and Matos (2006) document a cross-fund subsidisation strategy used by fund families to promote funds with high past performance through allocating new IPO shares. Nanda, Wang and Zheng (2004) suggest that fund families with star funds, i.e. funds with top ranking performance relative to peer funds that adopt the same investment style, attract considerably more new cash inflows than other type families. The growing cash inflows can bring new capital not only to the star funds but also to other funds within the same family, which brings about the spill-over effect. They also find evidence that star families tend to increase the volatility of cross-sectional returns in order to increase the odds of creating star funds.

Existing literature also discusses risk taking in the context of fund families. By referring to the traditional corporate tournament studies (for example Leonard, 1990; Gibbs, 1993), scholars have found that funds with distinct previous performance in the same family alter their risk exposure differently to compete for the benefits provided by the fund family (Kempf and Ruenzi, 2008), and such behaviour also occurs in funds with the same investment objectives (Brown et al. 1996; Busse, 2001; Schwarz, 2012). This type of competition, also known as the family tournament, is consistent with fund families' profit maximisation, taking into consideration the spill-over effect and the star funds phenomenon.

1.4.3 Managers' characteristics and performance shifting

The explanatory power of manager characteristics, including the manager's age, educational qualifications, tenure and level of risk taken, has been frequently visited in the prior literature. Analysing the cross-sectional fund returns, researchers have found that factors such as age and education level have a positive impact on fund performance.

In a seminal paper, Chevalier and Ellison (1999b) find evidence indicating that MBA managers outperform their non-MBA counterparts in fund performance. They also find that managers' age has a negative relationship with funds' performance, and explain this in terms of career concerns, whereby younger managers may work harder than older ones because they have a longer career life ahead of them and are more afraid of being fired for poor performance. This result confirms that of Chevalier and Ellison (1999a). With regard to their findings that the most robust performance difference can be found in managers' SAT scores, they explain that higher SAT institutions provide their graduates with indirect benefits in terms of social community, which means that they can obtain financial information from better sources. In addition, in their research to identify the relationship between risk holding and managers' characteristics, they suggest that a manager with an MBA or a high SAT score would possibly take more systematic risk; this is consistent with the research by Golec (1996). Their research also suggests that MBA managers are more likely to purchase low book-to-market ratio stocks and that older managers would have a greater tendency to use momentum strategies, but that age has a negative impact on fund performance.

Taking another perspective, Chevalier and Ellison (1999a) construct a research on mutual fund managers and their career concerns. Following the work by Fama (1980) and Lazear and Rosen (1981), they document that young managers are more likely to avoid high unsystematic risk, which is consistent with the finding by Chevalier and Ellison (1999b).

In addition to managers' characteristics, previous literature has established other factors that contribute to fund performance. Since such information is accessible to fund investors, it becomes part of the supplementary selection criteria for formulating fund investment decisions. However, existing research does not go deep enough to classify and analyse these factors at different levels. It remains unclear whether a better understanding of such factors would add value to actively managed funds.

1.4.4 Manager replacement and performance shifting

Given the influence exerted by managers' career concerns, it is also worth examining the effect of changing the fund managers on fund performance. As has been described above, actively managed funds come with managerial cost; hence, investors tend to select funds according to the managers' performance, and the selection by investors would have a feedback effect on managerial reshuffle through fund companies' administrative procedures. Given the influence both internally and externally, much attention has been paid to this area.

In an early research by Khorana (1996), significant evidence was found to support the hypothesis of presence of an inverse relationship between fund pre-replacement performance and the probability of managers' replacement. The author examined 339 US funds, which had all experienced management replacement during the sample period of 1979 to 1992; the result indicates that those funds had experienced two years' underperformance before the replacement month. In a subsequent research, Khorana (2001) goes further to analyse the post-replacement performance, based on the investigation into CEO turnover impacts by Denis and Denis (1995). After dividing the sample into two sub-groups according to their pre-replacement performance, Khorana (2001) documents that in the negative performance sample, alphas decrease in the pre-replacement period and recover after the replacement, while in the positive performance sample the return exhibits deterioration during the post-replacement period. This outcome implies that the market is effective in penalising underperforming managers under the extreme competition in the fund industry.

However, Khorana's work does not discuss the reason behind the deterioration in the positive performance sample during the post-replacement period.

More recently, Scherbina and Jin (2005) consider the influence of manager replacement on fund performance from the angle of portfolio holdings. Their result demonstrates that the disposition effect (the tendency to hold poor performing stocks for too long) exists in mutual fund managers' behaviour. Such an effect would reduce the fund performance, making appropriate replacement necessary. They find that new managers are more likely to change their inherited portfolio, and will sell a larger proportion of poor performing stocks than better stocks, which suggests the advisability of regular replacement of fund management. Furthermore, as changes to management may also be due to promotion and demotion, Evans (2009) suggests that manager's alpha should be seriously considered in the decision making process.

1.4.5 Organisation form and performance shifting

Fund management may take different organisational forms. Some fund companies, for example, do not appoint key individual managers, but instead set up a team to assume responsibility for fund governance. Researchers have attempted to study possible performance differences between these two forms. Prather and Middleton (2002), Chen, Hong, Huang and Kubik (2004) and Baer, Kempf and Ruenzi (2005) compare the performance of sole-managed and team-managed funds. Prather and Middleton (2002) find that, consistent with the classical decision making perspective, there is no difference in the performance of the two. Chen at al. (2004) and Baer et al. (2005) find evidence of underperformance in team-managed funds.

1.5 Organisation of the thesis

Tremendous efforts have been made in the existing literature to determine the factors that drive fund performance. Studies have also been initiated to devise methods of performance evaluation. This research intends to advance our knowledge in this field by focusing on three critical aspects of fund performance and methods of evaluation thereof: managers' turnover, fund family tournament and the investors' Bayesian learning.

1.5.1 Managers' turnover

The high liquidity of the fund industry and the competitive market for fund managers make it possible to test the effectiveness of the internal monitoring mechanism for unit trusts through a comparative analysis of fund performance around managers' replacement. Since open-end trusts allow unit holders to redeem their investment on demand, the consequence of poor fund performance will become visible when unit holders vote with their feet (Khorana, 1996). Such redemption could reduce the enhanced agency costs caused by failure of internal monitoring. In addition, evidence shows that there exists a significant positive relation between a fund's net cash flows and its performance (Ippolito, 1992; Sirri and Tufano, 1998; Berk and Green, 2004). This is because fund management companies benefit from managerial fees, which are proportional to the value of the fund's underlying assets. While investors face a variety of investment opportunities, fund companies are under pressure to appoint managers who can satisfy the fund companies' best interest. Thus, managers' dismissal based on historical underperformance becomes a reflection of effective managerial operation of fund companies. Given that skilful managers are more likely to be appointed by fund companies to improve fund performance, analysis of shifting performance around top managers' turnover offers a promising path to unearth evidence of effectiveness of the internal monitoring mechanism in the fund industry.

Whereas it has been demonstrated in the previous literature that poor fund performance will increase the probability of managerial replacement and that new managers tend to outperform old ones, studies to date are inconclusive about the efficiency of the administrative procedures in the UK fund industry. Specifically, many questions remain to be answered about whether the manager who is replaced really deserves demotion or dismissal, or whether it is due simply to the bad luck of a good manager before the reporting day. In the latter case, replacement may incur real losses. Moreover, as mentioned above, the new managers might be lucky enough to obtain superior returns, but this might not persist.

Against this backdrop, Chapter 2 of this research aims to improve our understanding of the corporate governance in the fund industry by examining the effectiveness of the internal monitoring and control system in the UK fund industry. First, we analyse the relation between top manager turnover and the performance of UK funds. We use a series of methods, including performance evaluation based on the factor models, percentile ranking, and sample matching tests. We divide funds that have experienced replacement of top managers into two time intervals or subsamples, namely the pre and post-replacement periods. A variety of methods are then applied to measure factors that affect the probability of replacement in the pre-replacement period. Second, we implement simulations to further examine whether UK fund companies can distinguish between managers with genuine skills and those who are lucky, or between poorly skilled managers and those who are unlucky. We conduct the bootstrapping simulation employed by Kosowski, Timmermann, Wermers and White (2006) and Cuthbertson, Nitzsche and O'Sullivan (2008) to determine whether fund companies can distinguish between poorly skilled managers and unlucky ones when deciding on managerial replacement. By comparing the actual estimation of abnormal performance with the 'luck' distribution given by bootstrapping simulations, we are able to distinguish the managers with 'real' stock-picking skills from those who are simply lucky. Hence, this method could provide additional evidence on the effectiveness of internal and external controls in the fund industry.

1.5.2 Family tournament, risk taking and performance consequences

Chapter 3 focuses on the tournament of funds within the fund family. Mutual funds alter their risk exposure frequently for various reasons. For example, funds may use risk shifting to indicate active trading or superior stock selection ability. In the context of the tournament theory, fund families allocate resources and information to the fund that can outperform peer funds within the same family. Hence, to a great extent it is the fund family that decides on which managers should be promoted or demoted based on the tournament outcome. As a result, managers should change their risk exposure only to improve the fund performance, rather than increase the overall uncertainty of the family.

While there is a large body of research that examines the characteristics of risk taking among funds, scant attention is paid to risk altering and its performance consequences. This motivates the discussions in Chapter 3. We first examine both the segment and family tournament phenomena in 3 IMA sectors of UK-domiciled equity funds from 2001 to 2010. The tournament analysis is conducted on the basis of both the raw returns and the risk-adjusted returns, to see how funds with distinct previous performance alter their future risk exposure. Then, we examine the performance consequences of such risk altering. Funds are ranked based on their performance and we compute the transition probability for each of the ranking groups. We also analyse the performance differences between funds with various levels of risk.

Research on risk taking from the perspective of fund families is sparse in the literature. We therefore deploy an empirical model to find out how the aggregated changes of fund ranks within the same family can be affected by the individual fund risk taking, as well as the cross-sectional family level of risk. In addition, we examine the characteristics of risk taking in the family tournament. Specifically, we discuss changes in both systematic and idiosyncratic risks, in order to shed light on managers' altering the portfolio holdings during the tournament.

1.5.3 Investor learning

Information from the fund family can provide critical insights on evaluating the performance of its component funds. The combination of fund family and the managers of its member funds contributes to yield the returns of a certain fund.

However, no adequate attempt has been made in the existing literature to take account of the information flowing from other peer funds as well as the family itself in the performance evaluation process.

In Chapter 4, we propose an evaluation process in a Bayesian framework to incorporate additional information provided by other members of the fund family in estimating their alphas using the factor model. We achieve this by adding another level to the conventional pricing model. Lindley and Smith (1972) derive a general solution to the two level linear model in a Bayesian system. However, the major problem lies in adding the proper prior information onto the covariance matrix of all the factors in the model. The conventional method applies a very restrictive prior belief to represent all the additional information. We relax this assumption by applying a separation strategy to decompose the covariance matrix into a diagonal matrix with variance of each factor, and a correlation matrix of all the factors in the pricing model (see for example Barnard, McCulloch and Meng, 2000; O'Malley and Zaslavsky, 2008). By so doing, we manage to incorporate the prior information given by the peer members of the family on each of the pricing factors, as well as the between-factor correlation in the estimation of fund alpha.

1.6 Main findings

1.6.1 Managers' turnover

Results from the analysis of managers' turnover and performance shifting in Chapter 2 suggest that managers' replacement can be predicted by historical poor performance. We also find that in the post-replacement period the previously inferior performance will be improved by the new managers. Results from the bootstrapping simulations suggest that managers with inferior previous performance driven by sample variation ('bad luck') are less likely to be replaced than are those with 'luck' driven superior performance. However, fund companies seem to be very generous towards those 'unlucky' managers in terms of managerial replacement. Furthermore, while most of the funds in the lower ranking group have replaced their 'lucky' or 'poorly skilled' managers with managers with genuine skills, the proportion decreases for funds with higher rankings.

With regard to the characteristics of portfolio holdings and to risk taking around the replacement, our results show that changes in the fund flows are negatively correlated with the probability of replacement. Meanwhile, superior managers tend to maintain their top holdings. Inferior managers, on the other hand, seem to lose confidence in their major holdings when, under the pressure of career concerns, they increase holdings of stocks other than the top ten assets in their portfolio.

1.6.2 Family tournament, risk taking and performance consequences

In Chapter 3, where we discuss risk taking behaviour and the performance consequences, our results show that high ranked funds are more likely to increase their risk exposure in the second half of the calendar year. Similar results are reported when funds are ranked by risk-adjusted returns. However, the risk seeking behaviour does not occur at the fund family level.

The findings are consistent with those of Mas-Colell, Whinston and Green (1995). Specifically, the winning funds in a small fund group are more likely to engage in a tournament with strategic interactions. Our results also imply the effects of employment concerns on fund risk taking. Although taking more risk can increase the probability of better performance, it can also come at the cost of performing even worse. Underperforming managers might value their employment more than do the top performing ones.

In terms of the performance consequence of risk shifting, our results suggest that the winning funds can outperform the losers by keeping a more stable risk level. This outcome persists when various performance evaluation models are employed. However, our results also suggest that winning funds deliver significantly higher alphas obtained from the conventional CAPM, the 3-factor and 4-factor models by taking more risk. We argue that the deterioration in the observed returns from increased holdings of the index-linked stocks could destroy the leading position held by the winning funds. The increased exposure of the winning funds to systematic risk shown in our results supports this finding. Moreover, in terms of the risk-adjusted returns, through taking more risk the winning managers achieve their goal of sending a signal to the fund company about their superior stock selection ability. In general our results agree with Huang et al. (2011), in that better performance comes with taking a more stable level of risk. However, we argue that risk taking might not necessarily be an indication of inferior performance, but can be regarded as the managers' intention to win the tournament at the cost of investors' benefits. Since managers' skills act as a crucial criterion for the fund family to decide which fund to advertise or to favour with extra resources, it stands to reason that winner funds would actively consider shifting risk exposure to retain their leading positions.

1.6.3 Bayesian learning and fund performance

In Chapter 4 we propose a general learning model to incorporate the information given by other funds within the same family. The results from the simulations suggest that the proposed evaluation method can better capture the learning process. We find that the posterior mean of fund alpha shrinks faster than reported by Jones and Shanken (2005), indicating that the evaluation results are more likely to be influenced by information given by the peer funds of the fund family. Another fascinating feature is that our method applies a full Bayesian treatment of all the pricing factors to grasp the prior information specific to each pricing factor. Our simulation shows that if the prior beliefs are reasonably accurate, this can improve the level of shrinkage to offer more precise evaluation results. Finally, since we decompose the individual fund alpha into the combination of the family mean and the idiosyncratic contribution from the manager, our empirical results also show that the fund manager contributes positively to the overall fund performance when non-informative prior beliefs are applied.

The rest of this thesis is organised as follows: In Chapter 2, we test the efficiency of the internal monitoring in the UK fund industry by examining whether managers possess genuine stock selection ability. In Chapter 3 we focus on managers' risk taking behaviour and the performance consequence in the fund family tournament. In Chapter 4 we propose a performance evaluation method in a Bayesian framework to incorporate additional information given by peer funds within the same fund family in estimating the funds' alphas. Conclusions and implications of this research are summarised in the final chapter.

CHAPTER TWO

MANAGERS' STOCK SELECTION SKILLS AND MANAGERIAL REPLACEMENT

2.1 Introduction

Mutual fund managers are appointed on their perceived specialist knowledge and information advantage (Gremillion, 2005). As they are usually not the major risk-bearers of the fund under their management, agency problems arise whereby without an effective control system, these managers may deviate from the interests of residual claimants or fund investors. The cost thus incurred by the funds could be considerable. To control such agency problems in the decision making process, Fama and Jensen (1983) show that it is essential to have an effective corporate governance system in which the internal monitoring mechanism plays a critical role. In the context of mutual funds, the internal monitoring mechanism involves measuring the performance of fund managers and implementing rewards and punishment, including dismissal. This internal monitoring, in tandem with the pressure exerted by the external managerial labour market through investors' hunting for better performing managers, drives the managers to satisfy the interests of the investors.

The extant literature has devoted great attention to evaluating the performance of mutual funds, using various assessment methods. Major research in this area includes Jensen (1968), Fama and French (1993), Carhart (1997), Grinblatt and Titman (1989, 1993), Goetzmann and Ibbotson (1994), Wermers (2000) and Pastor and Stambaugh (2002). In addition, past research has attempted to analyse the effectiveness of corporate governance in the fund industry. Several of them constructed the theoretical underpinning by connecting fund performance, optimal fund size, fund flows and portfolio characteristics with internal control in the fund industry, (e.g. Berk and Green (2004), Dangl et al. (2008)) and extensive empirical research devote much effort providing evidence to support such connection. (e.g. Chevalier and Ellison, 1999a; Khorana, 1996; Hu et al., 2000; Baks et al., 2007; Jin and Scherbina, 2005; Tonks, 2005; Shinozawa, 2007). These studies examine the efficacy of the fund industry's internal and external controls, with an overwhelming focus on the potential relation between performance of actively managed funds and the fate of their managers (Baks et al., 2007).

However, existing research is mainly concerned with the conventional notion of managers' performance, and overlooks the linkage between the managers' genuine skills and fund companies' decisions over appointments. This tends to bias analysis of the efficiency of fund industry governance. Moreover, conventional methods do not distinguish between performance that is related to genuine skills (good/bad), and mere sample variation. Hence, the previous literature seems hardly able to identify whether managers' performance is driven by luck or by their level of skill, nor whether managers should be rewarded or penalised accordingly. This shortcoming blurs the analysis of the efficiency of corporate governance in the fund industry.

Another under-researched area in the existing literature concerns the analysis of the relation between managerial replacement and portfolio characteristics such as exposure to idiosyncratic risk, portfolio holdings and portfolio leverage. Previous research argues that fund managers are likely to manipulate their risk profile by betting on the market to improve performance. It is suggested that risk shifting might be a signal of managers' opportunistic action or of their exceptional talent. Other research documents that the level of industry concentration in portfolios plays a crucial role in improving fund performance (Kacperczyk et al., 2005; Huang et al., 2011). Therefore, it is also crucial to examine managers' trading strategies under a given career concern. For example, will the manager increase his stock holding of a particular industrial sector, or will the fund increase leverage to satisfy investors' redemption needs?

The current research aims to improve our understanding of the corporate governance in the fund industry by shedding critical light on the effectiveness of the internal monitoring and control system in the UK equivalent of equity mutual funds, the UK equity unit trusts. First, we analyse the relation between top manager turnover and the performance of UK unit trusts. Focusing on the interaction between managerial replacement and fund performance, our research deploys a sample that covers the period from 1990 to 2009. Second, a simulation procedure is implemented to further test whether, in their managerial dismissal and appointment, UK fund companies can distinguish between managers with genuine skills and those who are lucky, or between poorly skilled managers and those who are unlucky.

To analyse top manager replacement we use a series of methods, including performance evaluation based on the factor models, percentile ranking, and sample matching tests. We divide funds that have experienced replacement of top managers into two time intervals or subsamples, namely the pre and post-replacement periods. A variety of methods are then applied to measure factors that affect the probability of replacement in the pre-replacement period.

To determine whether fund companies can distinguish between poorly skilled managers and unlucky ones when deciding on managerial replacement we conduct the bootstrapping simulation, as employed by Kosowski et al. (2006) and Cuthbertson et al. (2008). Research by Bickel and Freedman (1981) and Hall (1986) demonstrates that bootstrapping can improve approximation of the true distribution of funds' abnormal returns by recognising the thick tails among individual funds. By comparing the actual estimation of abnormal performance with the 'luck' distribution given by bootstrapping simulations, we are able to distinguish the managers with 'real' stock-picking skills from those who are simply lucky. Hence, this method could provide additional evidence on the effectiveness of internal and external controls in the fund industry.

Our results suggest that there exists a close relation between fund performance and top management turnover. We uncover evidence that managers' replacement can be predicted by historical poor performance. Also, results from the matching sample analysis indicate that the magnitude of decrease in the performance of the peer funds without replacement is considerably less than that of the funds in the replacement group. Fund companies will then try to improve the situation through managerial action. We find that in the post-replacement period the previously inferior performance will be improved by the newly installed management. Results from the bootstrapping simulation suggests that managers with inferior previous performance driven by sample variation ('bad luck') are less likely to be replaced than are those with 'luck' driven superior performance. However, fund companies seem to pay limited attention to managers with genuinely poor skills when making decisions in relation to managerial turnover. In the post-replacement period, most of the funds in the lower ranking group have replaced their 'lucky' or 'poorly skilled' managers with managers with genuine skills; however, the proportion shrinks for funds in the higher ranking groups.

In analysing managers' trading behaviour around replacement, our results show that there is significant difference in the influence of managers' risk taking, fund flow changes and portfolio composition of funds with different performance one year before the replacement. While flow changes are negatively correlated with the probability of managerial replacement, managers, the replacement probability for managers with inferior performance in the previous year is less sensitive to changes in fund flows. Superior managers tend to reduce their stock holdings of certain industrial sectors to lower the probability of being replaced. Meanwhile, increasing the holdings of the top ten assets in their portfolios reduces the funds' exposure to idiosyncratic risk but increases the replacement probability. As such, superior managers tend to maintain those among their top holdings that are in line with the fund's original investment objective. Inferior managers, on the other hand, seem to lose confidence in their major holdings when, under the pressure of career concerns, they increase holdings of stocks other than the top ten assets in their portfolio.

The remainder of this chapter is constructed as follows. The next two sections describe the methodology and data used in the research, respectively. Section 2.4 is mainly concerned with interpreting the results of the empirical investigation. The final section presents the conclusion.

2.2 Methodology

2.2.1 Performance evaluation

2.2.1.1 Objective adjusted returns

The objective adjusted returns (OAR) approach essentially analyses a firm's performance against a selected benchmark (Morck et al., 1990). This is calculated by taking the difference between annual holding returns of an individual fund and the benchmark. Formally, OAR is computed as follows:

$$OAR = \left[\prod_{t=1}^{12}(1+R_{i,t})-1\right] - \left[\prod_{t=1}^{12}(1+R_{b,t})-1\right] \quad (2.1)$$

where $R_{i,t}$ denotes the annual holding returns of an individual fund and $R_{b,t}$ is the annual holding returns on the benchmark. We define $R_{b,t}$ as the weighted average returns of all funds with the same investment objective for the corresponding year.

The OAR evaluates managers' performance against others in their peer group

(Khorana, 2001). Based on the signs of the OAR results, we sort the funds into a positive group (PG) and a negative group (NG), so that we can single out those funds that are ranked upper median among their peers.

2.2.1.2 Risk-adjusted returns

The risk-adjusted returns are based on factor models, including the single factor model and the Fama-French (1993) three factor model. The econometrical formulation of the latter is:

$$r_{i,t} = \alpha_i + \beta_i MKT_{i,t} + \beta_i^{HML} HML_{i,t} + \beta_i^{SMB} SMB_{i,t} + \varepsilon_{i,t} \qquad (2.2)$$

where α_i is the Jensen alpha measuring the risk-adjusted returns of fund i, $MKT_{i,t}$ is the excess market return; $HML_{i,t}$ is the return from the book to market portfolio; $SMB_{i,t}$ stands for the return from the size portfolio.

2.2.1.3 Percentile ranking

To develop a full perspective on the performance of individual funds as against the whole fund industry during the replacement period, we report and analyse the changes in percentile ranking based on the risk-adjusted returns around the top management turnover for every fund within its peer group. We additionally incorporate the ranking data from the Morningstar UK database, which give supplementary information on performance evaluation by independent financial media.

2.2.1.4 Matching sample analysis

Given that cross-sectional performance may experience mean reversion in a long time interval and that superior performance may not persist, we follow Denis and Denis (1995) and Khorana (2001) to adopt a matching sample analysis. This will enable us to identify whether the improvement or deterioration of performance in the post-replacement period is due to managerial efforts of the new managers, or is the result of mean reversion of securities' returns.

The matching sample analysis is based on the risk-adjusted returns of those funds that do not experience management turnover during the sample period. We first construct a sample of funds whose OAR (PG or NG) is similar with those funds in the turnover sample in the replacement period. Next, we calculate the 36-month abnormal performance in the pre-replacement period and 24-month performance in the post-replacement period for the funds in the matching sample. A particular fund will be used to match the manager-replaced fund only once. In other words, funds that have the same replacement date will share the same matching sample.

2.2.2 Determinants of the replacement

We examine determination of the management replacement by analysing the factors that are likely to be related to it. The replacement determinants may include genuine stock-picking skills, fund flow changes, risk shifting and portfolio holdings. Different from the performance shifting analysis, we follow the research by Chevalier and Ellison (1999b) to consider the managerial replacement on a calendar year basis.

2.2.2.1 Genuine stock-picking skills

Using conventional econometrical methods to evaluate abnormal returns of US and UK funds, most previous research finds no positive abnormal performance (alpha), even for the best funds. This raises the question of the very existence of skilled fund managers (Carhart, 1997), hence putting into doubt whether one can identify managers with genuine stock-picking skills. Furthermore, in previous management turnover analysis, no conclusive evidence has been found as to whether the abnormal performance is a factor in fund companies' decisions over replacement.

Recent research proposes that bootstrapping analysis may address this problem by separating managers with 'real' stock-picking skills from those who obtain superior performance only by chance. Therefore, we employ the bootstrapping method to examine the replacement decision in order to find out whether or not fund companies are able to dismiss non-skilled managers and appoint skilled ones.

Following the procedure of Kosowski et al. (2006) and Cuthbertson et al. (2008), we estimate the following three factor model, which is chosen as the basic model for our bootstrapping analysis:

$$\hat{r}_{i,t} = \hat{\alpha}_i + \hat{\beta}_i MKT_{i,t} + \hat{\beta}_i^{HML} HML_{i,t} + \hat{\beta}_i^{SMB} SMB_{i,t} + \hat{\varepsilon}_{i,t} \quad (2.3)$$

We divide all the funds with replacement into two groups: pre-replacement and post-replacement. For both groups, we estimate their abnormal returns $\hat{\alpha}_i$, the factor loadings and the residuals for each fund *i* through OLS regression. In the estimation, the residual term is given by $\{\hat{\varepsilon}^b_{i,t}, t = T_{i,1} \cdots T_{i,N}\}$, where $T_{i,1}$ and $T_{i,N}$ are the beginning and end dates, respectively, of the returns of fund i, and N is the sample size. These estimations are then saved for the later bootstrapping analysis.

In the bootstrapping simulation, we first construct a new sample of size N, i.e. $\{\varepsilon^b_{i,t}\}$ through re-sampling the saved residuals, where b stands for the times of re-sampling. Next, we create a time series of monthly returns for each fund i by setting the null hypothesis that $\hat{\alpha} = 0$, meaning that the manager of fund i has no stock-picking skills. The functional form of the analysis is:

$$r^b_{i,t} = \hat{\alpha}_i + \hat{\beta}_i MKT_{i,t} + \hat{\beta}_i^{HML} HML_{i,t} + \hat{\beta}_i^{SMB} SMB_{i,t} + \hat{\varepsilon}^b_{i,t} \quad (2.4)$$

where $r^b_{i,t}$ is the artificial returns of fund i with the true abnormal returns being equal to zero.

We regress $r^b_{i,t}$ on all the factors in the right-hand side of Equation (2.4) to estimate the bootstrapped alphas and the corresponding t-statistics. This procedure is applied to all the funds in the sample, including those without replacement. Thus, we can obtain the one-time bootstrapped alphas and the t-statistics for all funds. Repeating the above steps 1000 times, we then draw the distribution of bootstrapped alphas for each fund i. This distribution indicates the abnormal performance that is only due to sample variation.

To analyse the outgoing/incoming managers' genuine skills, we first estimate the conventional alphas and the t-statistics for each fund, with the estimation time being restricted to the fund's pre- and post-replacement periods. Then we rank the alphas and t-statistics of each replaced fund within its matching sample; for example the alpha of fund i is placed in the k^{th} percentile of its matching sample in terms of the sample's alpha. As we have already bootstrapped the alpha and t-statistic for each matching sample, we can draw the 'luck distribution' of fund i by using the alphas at the k^{th} percentile among all bootstrapped alphas in its matching sample.

Next we compare the fund's real alpha with the bootstrapped alpha/t-ratio distribution. If we find that the real alpha lies in the area greater than the 5% upper tail point of such bootstrapped alpha distribution, we reject the null that the abnormal performance is due to sample variation and conclude that the manager of this fund has genuine stock selection skills.

2.2.2.2 Fund flow changes

As a major indicator of managers' performance, changes in fund flow are closely monitored by fund companies. Dangl et al. (2008) suggest that manager replacement tends to be preceded by fund outflows and followed by fund inflows. This proposition concurs with Khorana's (2001) empirical finding. However, the extant literature generally documents a convex relation between fund performance and fund flow changes. Evidence shows that investors react asymmetrically to fund performance in that outperforming managers receive significant fund inflows while underperforming managers are not penalised equally with outflows (Sirri and Tufano, 1998). Therefore, replacement is not necessarily a direct result of changes in fund flow. Other factors, such as managers' genuine stock-picking skills and the age of the fund, may also have an impact on the convexity of the flow-performance relation and might influence fund companies' replacement decisions. Therefore, we include the managers' (funds') characteristics as interactive terms along with fund flow changes.

The estimation of fund flow is based on Huang et al. (2010), which is formulated as:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}(1 + R_{i,t})} \tag{2.5}$$

where $TNA_{i,t}$ is the total net assets for fund i at time t and $R_{i,t}$ is the fund's raw returns at time t.

2.2.2.3 Portfolio Holdings

Fund managers often switch their strategies, which leads to reallocation of their portfolio composition. We examine the changes in portfolio holdings focusing on the following aspects. First, we calculate the industrial concentration index (ICI hereafter) proposed by Kacperczyk and Sialm (2005). Empirical results show that underperforming managers tend to increase their holdings in small sized stocks while outperforming managers are likely to construct more concentrated portfolios within certain industries. By including the evaluation of ICI in the management replacement analysis, we can further examine the implications of such holding adjustment behaviour for management replacement.

Calculation of the industrial concentration index (ICI) is as follows:

$$ICI_{i,t} = \sum_{i=1}^{12} (w_{i,t} - \bar{w}_{i,t})^2 \tag{2.6}$$

where $w_{i,t}$ is the weight of the value of each of the 12 industries held by fund i and $\bar{w}_{i,t}$ is the value weight of the certain industry in the entire stock market.

Second, we extend Equation (2.6) to measure allocation shifts between equity and cash in the fund's portfolio. Berk and Green (2004) argue that, given decreasing returns to scale on the actively managed portfolio, fund managers may switch their holdings between actively and passively managed portfolios in the fund's holdings to satisfy certain investment objectives. However, in the context of management replacement, certain trade-offs may exist in managers' decisions over portfolio composition. Underperforming managers may choose to keep betting on the market by increasing their holdings of equity, but they cannot escape the pressure arising from the need to hold cash for investors' potential redemption. Therefore, we also include the funds' debt to capital ratio to reflect managers' cash/equity allocation around the replacement.

2.3 Data

2.3.1 Sample description

We start our sample construction with the data of replacement series, which are collected from the Morningstar UK database using information of the specific day on which the current fund managers first took over operation of the funds. In analysing managers' stock-picking skills, we focus on the performance of UK domiciled equity unit trusts and open-ended investment companies (OEICs) which conduct their investment business primarily in the UK equity market. These funds differ from closed-ended funds in that they can only be traded between the trust companies and investors.

Funds with anonymous managers and management groups have been screened out from the sample, since we consider the stock-picking skills of specific managers or a solo manager. By the same reasoning, we also exclude index tracking funds. As a result, we find in the Morningstar database 386 funds which have experienced top manager replacement.

From these 386 funds, we then select funds that have at least 5 years' performance history. Specifically, the sample includes funds with at least 3 years' performance history preceding the replacement month and 2 years' data after the replacement. This has the advantage of avoiding small sample bias. The replacement sample that meets our data screening criteria comprises 218 funds from four sectors. The IMA categorises UK equity unit trusts and OEICs into four sectors, which we follow. Specifically, our sample includes 120 funds from the UK All Companies sector, 54 funds from UK Equity Income, and 5 funds from the UK Equity Income and Growth. The remaining funds are from UK Small Companies.

The returns data for analysing performance of individual funds are also collected from Morningstar. Monthly returns of all funds are calculated by dividing changes in monthly net asset value, returns from reinvesting all income, and capital gain distributions, by the starting NAV of the month. They are not adjusted by sales charges in the total returns. However, the management and administrative fees are deducted from the total returns, so that the performance evaluation can provide evidence on whether the funds are profitable for investors.

To evaluate funds' abnormal returns we follow standard factor models, for example the Fama and French (1993) three factor model and the Carhart (1997) four factor model. The market benchmark used is the FTSE all share index. The value factor, also known as HML, is derived by deducting monthly returns on the UK value index compiled by Morgan Stanley Capital International (MSCI) from the returns of the MSCI growth index. The size factor is the difference between monthly returns of the Hoare Govett Small Companies (HGSC) index and the returns on the FTSE 100 index. The mimicking portfolio for the Carhart (1997) momentum effect, or the UMD factor, is constructed by using the total return index data for all UK listed equities. It is given by monthly average returns of a weighted portfolio measured by taking the difference between the returns of the top and bottom 30% of stocks. Finally, the market excess returns are calculated on the basis of monthly data of the 3-month UK Treasury Bill.

2.3.2 The survivorship bias issue

To investigate possible survivorship bias in our sample of 218 funds, we carry out a preliminary test. Table 2.1 displays the results.

Table 2.1 Summary Statistics

Replacement Time (Pre)	Number of Funds		Alpha (3 Factor)		Alpha (4 Factor)	
Panel A	obs≥1	obs≥36	obs≥1	obs≥36	obs≥1	obs≥36
All Investment Objectives						
~1998	6	6	-0.6385	-0.6385	-0.6306	-0.6306
1999~2002	75	73	-0.4645	-0.4485	-0.464	-0.4598
2003~2006	146	144	0.7530	0.7559	0.7650	0.7789
2007~2009	115	107	0.2890	0.2749	0.2770	0.2790
UK All Companies						
~1998	1	1	-0.6114	-0.6114	-0.6348	-0.6348
1999~2002	37	35	-0.1817	-0.1811	-0.1970	-0.1867
2003~2006	81	81	-0.0593	-0.0593	-0.0593	-0.0593
2007~2009	85	77	-0.0974	-0.092	-0.091	-0.0904
UK Equity Income						
~1998	-	-	-	-	-	-
1999~2002	13	13	0.2840	0.2840	0.2735	0.2735
2003~2006	41	41	-0.2219	-0.2219	-0.2110	-0.2110
2007~2009	21	21	-0.1324	-0.1324	-0.1301	-0.1301
UK Equity Income & Growth						
~1998	-	-	-	-	-	-
1999~2002	6	6	-0.1285	-0.1285	-0.1307	-0.1307
2003~2006	5	3	-0.0593	-0.0699	-0.0603	-0.0612
2007~2009	-	-	-	-	-	-
UK Smaller Companies						
~1998	5	5	-0.2247	-0.2247	-0.2529	-0.2529
1999~2002	19	19	-0.0963	-0.0963	0.0899	0.0899
2003~2006	19	19	0.1014	0.1014	0.0784	0.0784
2007~2009	9	9	0.2245	0.2245	0.2587	0.2587

(Continued on next page)

Table 2.1 Summary Statistics (Continued)

Replacement Date (Post)	Number of Funds		Alpha (3 Factor)		Alpha (4 Factor)	
Panel B	obs≥1	obs≥24	obs≥1	obs≥24	obs≥1	obs≥24
All Investment Objectives						
~1998	6	6	-0.6104	-0.6104	-0.6065	-0.6065
1999~2002	75	75	-0.4507	-0.4507	-0.4101	-0.4101
2003~2006	146	146	0.7530	0.7530	0.7015	0.7015
2007~2009	115	27	0.3190	0.2977	0.3010	0.2649
UK All Companies						
~1998	1	1	-0.5872	-0.5872	-0.4793	-0.4793
1999~2002	37	37	-0.1817	-0.1817	-0.198	-0.198
2003~2006	81	81	-0.0478	-0.0478	-0.0359	-0.0359
2007~2009	85	25	-0.0743	-0.0635	-0.0847	-0.0727
UK Equity Income						
~1998	-	-	-	-	-	-
1999~2002	13	13	0.2721	0.2721	0.3045	0.3045
2003~2006	41	41	-0.2107	-0.2107	-0.2344	-0.2344
2007~2009	21	2	-0.1104	-0.1012	-0.1621	-0.1453
UK Equity Income & Growth						
~1998	-	-	-	-	-	-
1999~2002	6	6	-0.1024	-0.1024	-0.1185	-0.1185
2003~2006	5	5	-0.0364	-0.0364	-0.0292	-0.0292
2007~2009	-	-	-	-	-	-
UK Smaller Companies						
~1998	5	5	-0.2187	-0.2187	-0.2798	-0.2798
1999~2002	19	19	-0.0765	-0.0765	0.0569	0.0569
2003~2006	19	19	0.0978	0.0978	0.0876	0.0876
2007~2009	9	-	0.0345	-	0.0467	-

Notes: Funds in the table are classified according to their investment objectives defined as IMA. They are also sorted into two groups, i.e. all the funds that have experienced managerial replacement (obs≥1), and the funds that are included in our sample (obs≥36/24). The table also provides the number of observations of the replacement in five time periods. Estimated alphas using the three factor and four factor models are reported for each type of fund.

From Table 2.1, it can be seen that the difference between all funds that have replacement experience and the sample funds is moderate, particularly in terms of the number of observations. Columns 1 and 6 report the number of funds that have experienced manager replacement for all investment objectives in the pre- and post-replacement periods. During 2007-2009, the difference in numbers between all funds and the sample funds is relatively large. However, as Columns 2 and 7 suggest, this is because some of the funds from the UK All Companies category replaced their managers in late 2007, which means that they have less than 2-years' return data and so are disqualified from our sample.

Table 2.1 also provides the comparison of abnormal performance based on the three and four factor models. It can be seen that, for all investment objectives across the board, the alphas estimated for funds with obs≥1 and with obs≥36/24 do not differ significantly. This confirms that the sample does not suffer from survivorship bias.

2.4 Empirical results

2.4.1 Performance changes around replacement

One central concern of the literature of top manager turnover in the fund industry is performance changes before and after the replacement. To investigate this matter, we deploy the methodology discussed above to collect return data of the funds three years before and two years after the replacement. Four evaluation methods, i.e. the factor model, the total returns measure, the percentile rankings measure and the matched sample performance measure, are then applied to these data. The ensuing estimation results are classified into a positive group (PG) and a negative group (NG), based on the signs of individual funds' objective-adjusted returns in the pre-replacement period. The results indicate that while NG funds experience a significant performance decline before the replacement, their performance tends to recover post-replacement.

As shown in Panel A of Table 2.2, estimates from the factor models provide more pronounced results than those of the other models. It comes as no surprise that, based on the outcome of the three factor model, NG funds' abnormal returns drop by an average of 33 basis points in the year [-3,-2], with a further 1 basis point drop in the year [-2,-1]. In the post-replacement period, results from the three factor model suggest a sizeable improvement of 60 basis points for the year [0, +1] and a cumulative improvement of 72 basis points for the year [0, +2].

Table 2.2 Analytics of Top Management Turnover

Panel A	3 Factor Model		4 Factor Model		Total Returns		Ranking		Matched Sample	
	PG	NG	PG	NG	PG	NG	PG	NG	PG	NG
year-3	0.0018	0.0011	0.0239	0.1166	0.0082	0.0076	0.5121	0.4937	0.0025	-0.0014
	(0.0013)	(0.0006)	(-0.0029)	(-0.0065)	(0.0079)	(0.0086)	(0.5020)	(0.4100)	(0.0026)	(-0.0014)
year-2	0.0016	-0.0021	0.0096	-0.0116	0.0036	0.0036	0.5472	0.3843	0.0022	-0.0020
	(0.0012)	(-0.0010)	(0.0067)	(-0.0072)	(0.0074)	(0.0114)	(0.5740)	(0.3130)	(0.0018)	(-0.0018)
year-1	0.0026	-0.0022	0.0063	-0.1026	0.0061	0.0077	0.6164	0.4148	0.0019	-0.0022
	(0.0026)	(-0.0006)	(-0.0128)	(-0.016)	(0.0119)	(0.0126)	(0.7300)	(0.4950)	(0.0017)	(-0.0019)
year0	0.0012	-0.0037	0.045	-0.0504	0.0041	0.0012	0.6170	0.4240	0.0017	-0.0023
	(0.0013)	(-0.0026)	(-0.0019)	(-0.0379)	(0.0142)	(0.0031)	(0.7289)	(0.4137)	(0.0015)	(-0.0018)
year+1	0.0023	0.0022	-0.0503	-0.0354	0.0073	0.0055	0.6175	0.6068	0.0009	0.0001
	(0.0022)	(0.0013)	(-0.0373)	(-0.0171)	(0.0102)	(0.0059)	(0.6610)	(0.6800)	(0.0007)	(-0.0010)
year+2	0.0022	0.0035	-0.0529	-0.0137	0.0032	-0.0068	0.6056	0.5347	0.0010	0.0013
	(0.0013)	(0.0039)	(-0.0181)	(-0.0336)	(0.0086)	(-0.0089)	(0.7070)	(0.6170)	(0.0004)	(0.0013)

(Continued on next page)

Table 2.2 Analytics of Top Management Turnover (Continued)

Panel B	3 Factor Model		4 Factor Model		Total Return		Ranking		Matched Sample	
100%	PG	NG	PG	NG	PG	NG	PG	NG	PG	NG
-3 to -2	-0.1268	-2.9436**	-0.5983	1.0995**	-0.5669	-0.5244	0.0685	-0.2216**	-0.1560	-0.3902
	(-0.0917)	(-2.7370)	(3.3103)	(-0.1077)	(-0.0684)	(0.3347)	(0.1434)	(-0.2366)	(-0.3221)	(-0.3312)
-3 to -1	0.4165	-2.9501**	-0.7364	1.8799**	-0.2554	0.0094	0.2036**	-0.1598	-0.2450*	-0.5024
	(0.9389)	(-2.0240)	(-3.4138)	(-1.4615)	(0.5104)	(0.4663)	(0.4542)	(0.2073)	(-0.3487)	(-0.4003)
-3 to +1	0.2411	0.9653	-3.1046**	1.3036**	-0.1134	-0.2785	0.2058**	0.2291**	-0.6378**	1.0990**
	(0.6674)	(1.2542)	(-11.8621)	(-1.6308)	(0.2905)	(-0.3114)	(0.3167)	(0.6585)	(-0.7225)	(0.2551)
-2 to +1	0.4212	2.0111**	-6.2396**	2.0517**	1.0469	0.5169	0.1285*	0.5789**	-0.5708**	1.0712**
	(0.8357)	(2.2978)	(-6.5672)	(-1.3750)	(0.3853)	(-0.4841)	(0.1516)	(1.1725)	(-0.5906)	(0.4404)
-1 to +1	-0.1238	2.0078**	-8.9841**	0.6550	0.1907	-0.2853	0.0018	0.4628**	-0.5202**	1.0659**
	(-0.1400)	(3.2014)	(-1.9141)	(-0.0688)	(-0.1456)	(-0.5304)	(-0.0945)	(0.3737)	(-0.5739)	(0.4680)
+1 to +2	-0.0257	0.5920*	-0.0517	0.6130	-0.5616	-2.2364	-0.0193	-0.1189*	0.0760	7.7497*
	(-0.4282)	(2.0232)	(0.5147)	(-0.9649)	(-0.1569)	(-2.5085)	(0.0696)	(-0.0926)	(-0.4296)	(2.2851)
Obs.	127	91	127	91	127	91	127	91	127	91

Notes: Reported are the means of the performance of a sample of 218 unit trusts and OEICs in terms of abnormal returns. Medians are in brackets. The results are based on the three factor model, the four factor model, the measure of total returns, percentile rankings and matched sample performance measurement. PG stands for the positive returns group and NG for the group with negative returns. The grouping is dependent on individual funds' objective-adjusted returns in the three years before the replacement. Panel A reports the level of the index in the sample period and Panel B provides its percentage changes across each event window around a replacement date. ** and * indicate statistical significance at 1% and 5% levels respectively, based on paired T tests.

However, for the PG group, Panel A indicates only a moderate increase in abnormal returns in the interval of years [-3, -1]. Despite a sharp drop in the replacement month, performance returns swiftly to the level attained by the previous management in the pre-replacement period. For example, in the year [0, +1] the abnormal returns increase from 0.0012 (year 0) to 0.0023 (year +1) and remain almost unchanged in year +2. A possible reason for this lies in the fact that the PG funds had a good performance record before the replacement and so the incoming managers may find it unnecessary to change the composition of the original portfolios. Results from the four factor model show a similar outcome for the NG group, but indicate a rapid decline in the PG group's performance throughout the sample period. Moreover, almost all abnormal returns calculated under the four factor model are consistently and statistically insignificant, which is consistent with the results in previous research on the selection of models on mutual funds. Blake and Timmermann (1998), Quigley and Sinquefield (2000), Tonks (2005) and Cuthbertson et al. (2008) suggest that the momentum variable is not prevalent in the UK fund industry. Bearing this in mind, in what follows we will be mainly concerned with the three factor model.

The post-replacement improvement is also reflected in the percentile rankings of funds' abnormal returns (from lowest to highest), as shown in Panel A. It is not surprising to see that the NG group experiences a significant increase in cross-sectional ranking during year [-1, +1], since the ranking is based on abnormal returns estimated by the three factor model. However, given the results in the year [+1, +2], the growth will not persist.

Turning to the measure of total returns, the outcome becomes more fluctuant. This implies that total returns may not be a major concern in fund companies' decisions on managers' replacement. Assuming that in general efficient internal controls are in place in the UK fund operations, our results do not concur with the proposal in favour of evaluating fund performance in terms of their total returns.

The matched sample performance measure in Panel A sheds additional light on the value-added feature of manager replacement. The trend of performance changes of the matched sample in the NG group in the pre- and post-replacement periods closely matches that of the changes in abnormal returns. This suggests that further analysis of those matched samples would provide additional evidence for whether or not the replacement is a value-added activity. Since no replacement has taken place in the matched sample, if the performance change generated by replacement is less than the performance improvement in the matched sample, we cannot regard such replacement as adding value.

Panel B of Table 2.2 compares the changes in level of performance in terms of the four different measurements. The levels of change for the NG replacement group are 201.11% and 200.78% during the intervals [-2, +1] and [-1, +1], respectively. In comparison, the NG matched sample shows corresponding changes of 107.12% and 106.59%. Hence the turnover generated by top manager replacement seems to add more value than in those funds that have the same pattern of OAR but choose not to replace their managers. Moreover, there is a marginal decline in the decreasing rate of abnormal returns in the post-replacement period for both groups, especially the NG group. This outcome is robust when checking with the four factor model. One possible explanation for this effect is the influence of window-dressing. Managers may construct a more risky portfolio to window-dress the performance record before the reporting date, leading to a marginal decrease in each of the measures before the replacement.

Further evidence of performance switching can be found from the rating data. Table 2.3 summarises the historical rating from Morningstar for the unit trusts and OEICs in our sample. With the exception of UK Equity Income funds, both NG and PG funds receive upgrading of their ratings after the managers are replaced. In comparison, in Table 2.1, we find that only the NG group shows enhanced performance, as the new managers tend to change the composition of portfolios constructed by the former management, while the PG group shows no such improvement, since the new managers may retain the inherited portfolio structure.

Table 2.3 Rating Analysis of Management Turnover

Rating	Whole Sample		UK All Companies		UK Equity Income		UK Equity Income & Growth		UK Smaller Companies	
Year	PG	NG	PG	NG	PG	NG	PG	NG	PG	NG
-3 to 0	3.1979	2.8734	3.0511	2.8204	3.4572	3.3676	2.4444	2.4444	3.2087	2.6520
	(3.0909)	(2.9231)	(3.0000)	(2.9009)	(3.5000)	(3.3676)	(2.8333)	(2.4444)	(3.2087)	(2.6520)
0 to +2	3.4820	2.9147	3.5721	2.9974	3.3493	2.6246	3.7668	3.0564	3.4041	2.6689
	(3.4194)	(2.8534)	(3.6250)	(2.9463)	(3.4231)	(2.6246)	(3.8760)	(2.2800)	(3.4041)	(2.6489)

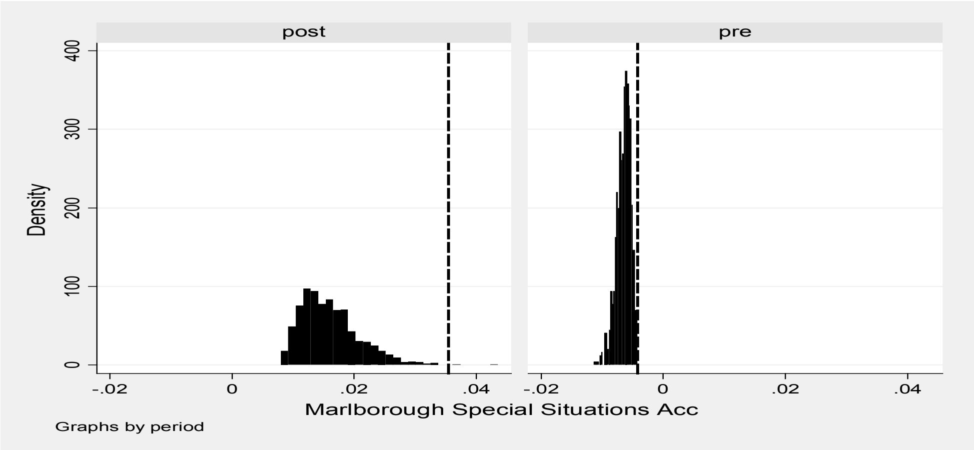
Notes: Reported are the mean ratings of UK unit trusts and OEICs. Medians are in brackets. The data are sourced from the Morningstar, and cover the pre and post- managerial replacement periods. The funds are sorted according to IMA investment objectives. PG stands for the positive returns group and NG for the group with negative returns. The division of the groups is dependent on individual funds' objective-adjusted returns in the three years before the replacement. The Morningstar ratings for funds go from 1 (minimum) to 5 (maximum).

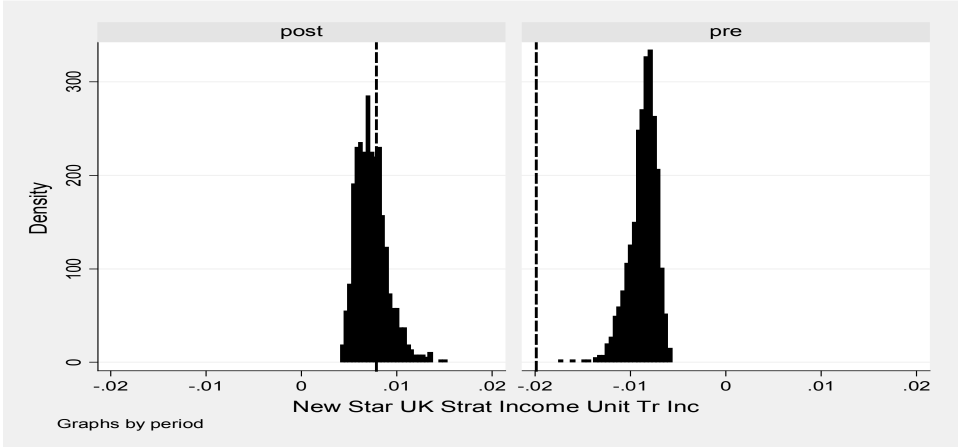
2.4.2 Determinants of managerial replacement

2.4.2.1 Genuine stock selection skill

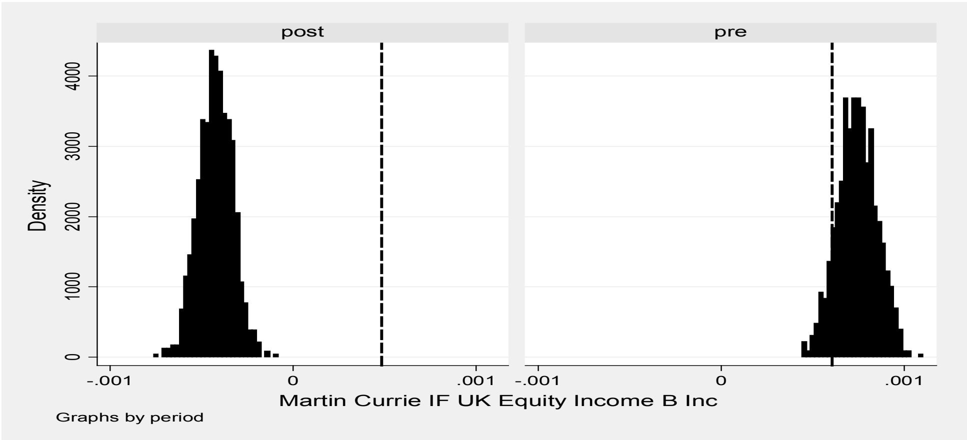
We apply the bootstrapping procedure to verify managers' genuine stock selection skill. Bootstrapping can simulate abnormal performance that is solely due to sample variation, or 'luck distribution'. With this method, underperforming managers whose performance has been classified as due to genuinely poor skills should expect a higher probability of managerial replacement; however, for 'unlucky' managers, the probability of their replacement should not be as high.

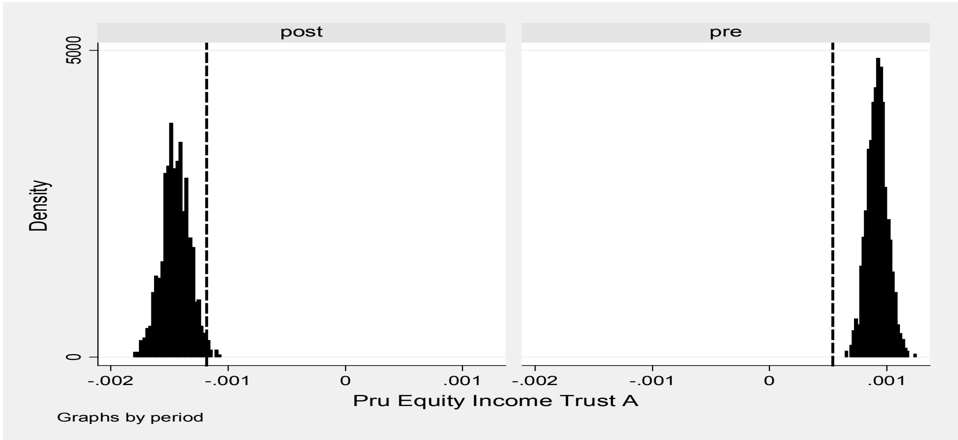
As an example of bootstrapping simulation, Figure 2.1 shows the comparison between the funds' actual alphas plus t ratios and their corresponding bootstrapped ones. Panel C2 of Figure 2.1 plots the performance due to luck, since actual alphas of these funds lie within the 95% percentile of the 'luck distribution'. After the replacement, however, the rank of the funds experiences a remarkable advance as the incoming managers are more capable of selecting stocks (see Panel A1 of Figure 2.1). In such cases the replacement decision signals effective internal controls within the fund company. Figure 2.2 displays the comparison between actual t ratios of the sample alphas and the bootstrapped ones. Panel C2 of Figure 2.2 presents the case where the performance of the funds is driven by sample variation rather than by the genuine skills. The outcome of Panel C2 is consistent with that of C2 of Figure 2.1.





Panel A1: Top one Panel A2: Bottom 0.3% Panel B1: Top one Panel B2: Bottom 0.4%

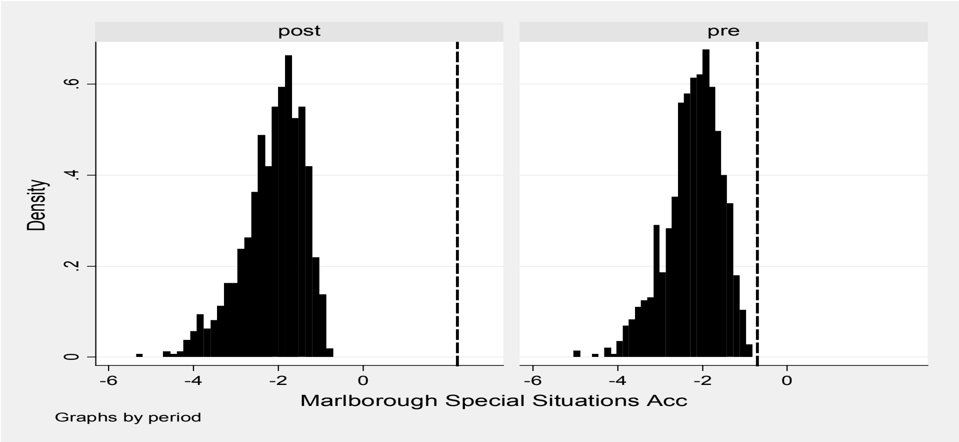




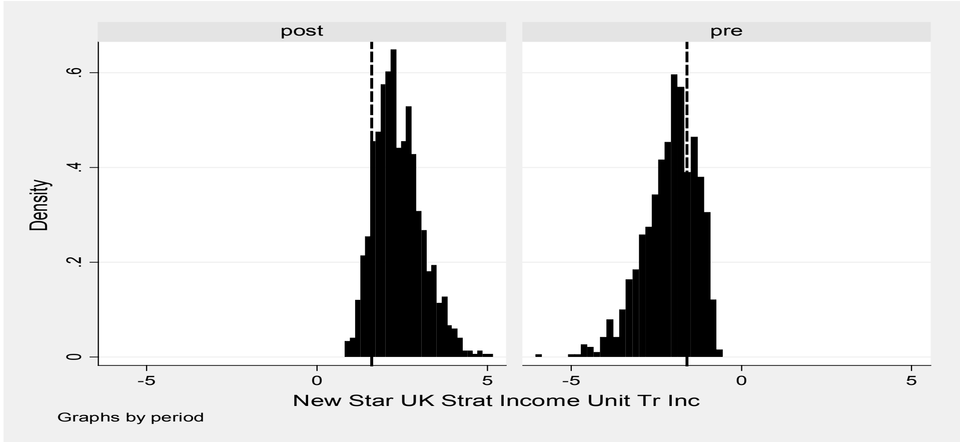
Panel C1: Bottom 40.9% Panel C2: Top 65.5% Panel D1: Bottom 25.4% Panel D2: Top 70.1%

Figure 2.1 Histogram of Actual Alphas against Matching Bootstrapped Alphas around Replacement Time

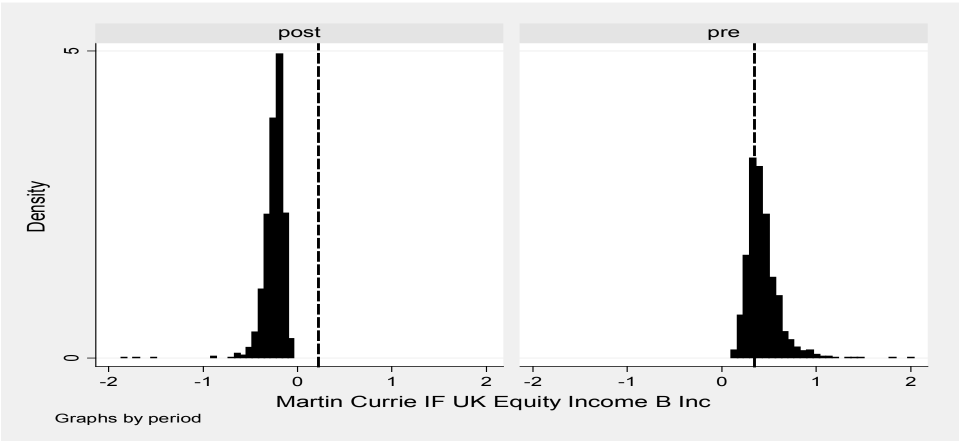
Notes: Figure 2.1 shows the histogram of the funds' actual alphas against their matching bootstrapped alphas around the replacement time. The vertical line gives the actual alphas obtained from estimation of the three factor model on funds with negative ORA. The selection of the funds to form bootstrapped alphas is based on their matching counterparts in the replacement group.



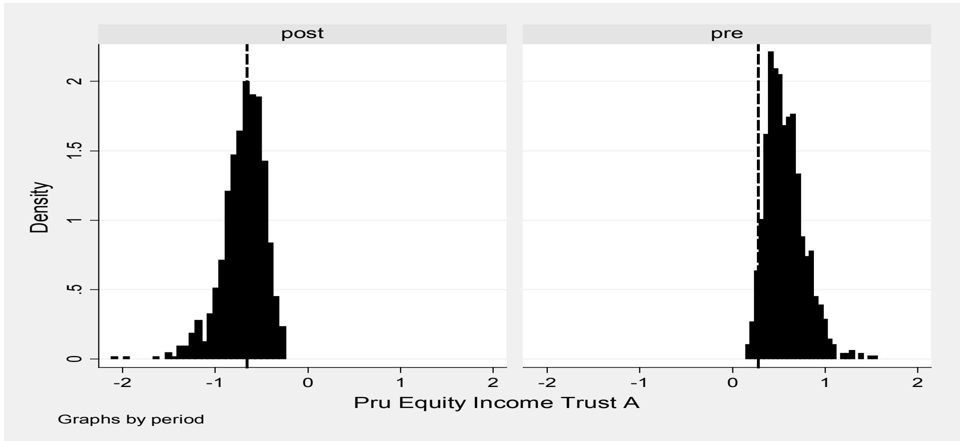
Panel A1: Top one
Panel A2: Bottom 0.3%



Panel B1: Top one
Panel B2: Bottom 0.4%



Panel C1: Bottom 40.9%
Panel C2: Top 65.5%



Panel D1: Bottom 25.4%
Panel D2: Top 70.1%

Figure 2.2 Histogram of Actual Alphas' t-ratio against Matching Bootstrapped Alphas' t-ratio around Replacement Time

Notes: Figure 2.2 shows the histogram of the funds' actual t-ratios against their matching bootstrapped ones around the replacement period. The vertical line gives the actual t-ratios obtained from estimation of the three factor model on funds with negative ORA. The funds selected to form the bootstrapped t-ratios are based on the matching sample of each fund in the replacement group.

Table 2.4 reports the general results from bootstrapping simulation of funds' abnormal performance. We rank the whole sample into ten percentile groups according to their abnormal performance. The ranking is listed from the worst to the best performers. The first row shows the probability of replacement for funds with different performance status, i.e. driven by 'luck' or by genuine skills. In the group of funds whose managers are judged to have genuine stock-picking skills, less than 20% of the funds located in the lower 30% of the percentile ranking have experienced managerial replacement. For funds with higher ranking, above 80% in the percentile ranking, the proportion grows to almost 25%. The results for funds in the sample variation group show a similarly low proportion for funds with lower ranking. Particularly, none of the managers ranked below 10% have been replaced by the management companies. But almost 35% of the 'lucky' managers have been replaced, despite their delivering higher-ranked abnormal returns. This result indicates that many fund companies are not captivated by the 'lucky' managers' extreme performance, and over 85% of the companies would choose to give 'unlucky' managers another chance. However, the corresponding proportion of the skilled managers' group is not significantly different within each percentile ranking group, which suggests that fund companies pay less attention to previous year ranking when making the replacement decision if the managers' performance is attributed to genuine skills.

Table 2.4 Proportion of Funds with Genuine Stock Selection Skills

	Genuine skills	Percentile Ranking (Low to high) Below 10%	<20%	<30%	<40%	<50%	<60%	<70%	<80%	<90%	<100%
Probability of replacement	Yes	0.0574	0.0588	0.0575	0.0466	0.1226	0.0722	0.0774	0.0956	0.0826	0.0967
	No	0.0000	0.1064	0.0256	0.1250	0.0917	0.0881	0.0816	0.2727	0.0000	0.0781
Genuinely unskilful to genuinely Skilful	-	0.6667	0.7500	0.6923	0.7857	0.6154	0.5000	0.3214	0.0000	0.0952	0.2222
'Lucky' to genuinely skilful	-	-	0.8000	1	1	0.6667	0.5263	0.0000	0.0000	-	0.0000
Total replaced fund	-	234	251	265	375	438	490	488	452	383	333

Notes: The table reports the bootstrapping results for all the funds whose managers were replaced. Funds have been sorted into 10 groups by their performance before replacement, e.g. the group below 10% includes funds that lie in the lowest 10% of the performance ranking in that calendar year. The first row reports the proportions of genuinely skilful (lucky) managers being replaced in the entire fund sample, where Yes (No) stands for managers that can be classified as genuinely skilful (lucky). The 2nd and 3rd rows report the consequences of managerial replacement, i.e. the proportion of genuinely non-skilful/unlucky managers replaced with genuinely skilful ones and the last row reports the total number of funds which have experienced replacement in each group.

We further apply the bootstrapping technique to simulate the 'luck distribution' for the funds in the post-replacement period. The results reported in the second and third rows of Table 2.4 document the proportion of funds that have improved their performance after the unskilful/lucky managers have been replaced by managers who are genuinely skilled. The results show that over 65% of the funds have successfully replaced their unskilful managers with better ones. For the group of 'unlucky' managers this proportion increases to over 80%. However, funds in higher ranks have been subject to only a limited number of replacements and good succeeding managers, particularly when the abnormal performance during pre-replacement was regarded as luck driven.

A possible explanation for this difference is the difficulty that the incoming managers may run into when trying to keep the funds' returns at the original high level, particularly for managers in the 'lucky' group. In our sample, 27% of the funds with 'lucky' managers experienced replacement, but none of them found skilful substitutions. Alternatively, the management companies may be capable of recognising extreme performance resulting from sample variation and of initiating managerial replacement, but the new managers may adjust the portfolio composition only marginally. This provides additional support for changing the 'lucky' managers.

An alternative approach to explaining the bootstrapping simulation is to compare the true and bootstrapped alphas of the entire replacement group. In Figures 2.3 and 2.4 we apply the kernel density estimation to find how many manager replaced funds are able to achieve superior performance through managers' genuine stock-picking skills. Figure 2.3 compares the distribution of true (the solid line) and simulated alphas (the dashed line) in the pre-replacement period. The entire performance distribution shown in Figure 2.3 is right-skewed from the origin. Only a limited section of the solid line matches the dashed line in the left tail. In most cases the solid line fluctuates around the dashed line in both tails, suggesting that for most of the replaced managers their inferior performance can be attributed not to 'bad luck' but to their poor skills. Moreover, in the post-replacement period (Figure 2.3), the dashed line largely deviates from the solid one in both tails, especially in the right tail of the distribution, meaning that many of the incoming managers achieve their outperformance through genuine stock-picking skills. Such findings are consistent with the results given in Table 2.4.

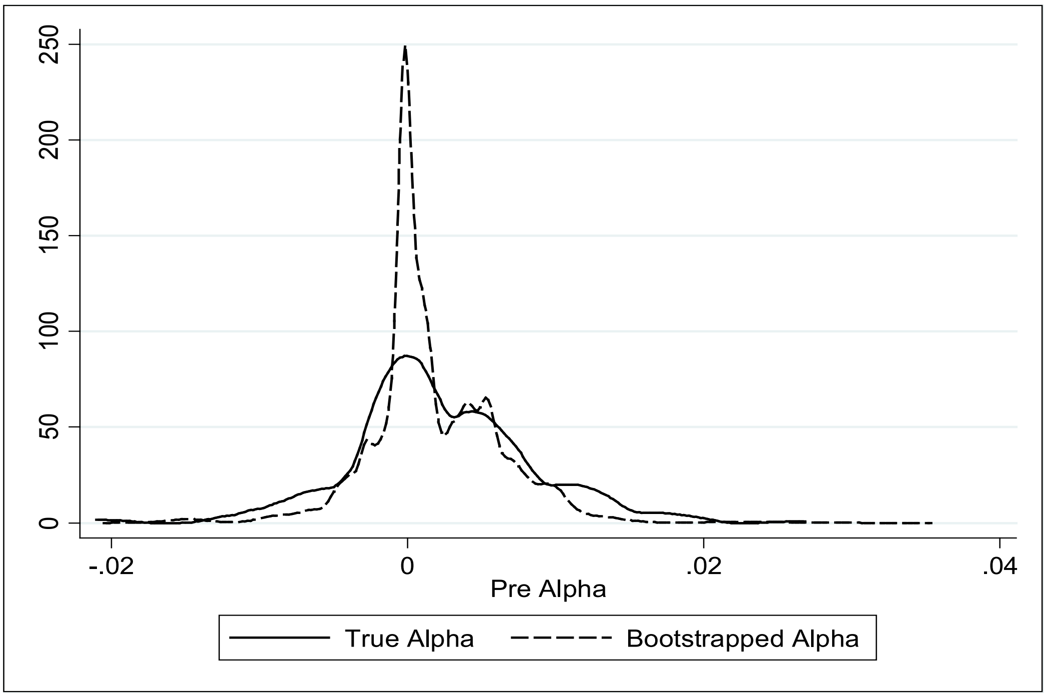


Figure 2.3 Kernel Density Estimation of Abnormal Performance in Pre-Replacement Period

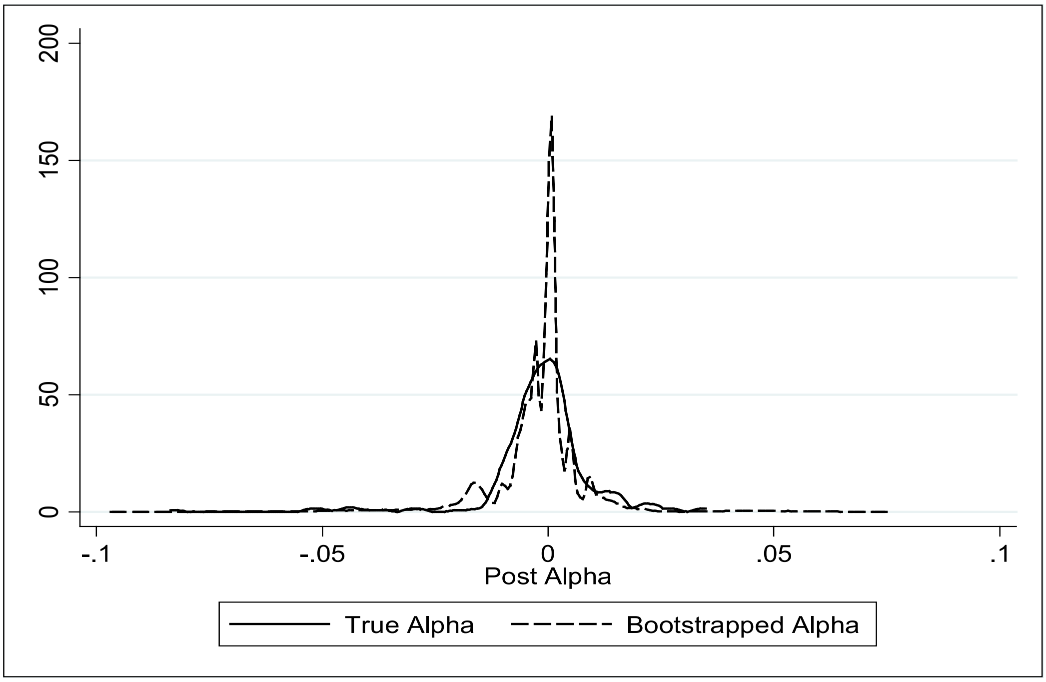


Figure 2.4 Kernel Density Estimation of Abnormal Performance in Post-Replacement Period

The bootstrapping simulations generally indicate that fund management companies are able to identify managers whose performance is the consequence of sample variation. They would replace the managers with higher ranking since such 'lucky' over- performance might suffer from future fluctuations of the returns. Meanwhile, the 'unlucky' managers will be retained for a 'second chance'. However, fund companies seem to pay less attention to these poorly skilled managers. We will look into this further by combining the analyses of flow changes and portfolio holding. In addition, our results show that although a better successor would improve the fund's performance, replacement can still be regarded as a 'costly firing', particularly for funds with higher rankings.

2.4.2.2 Managerial replacement-flow relationship

To analyse determinants of managerial replacement, we set up a series of evaluation models based on the Probit framework. The main mission is to evaluate the interaction between the probability of managerial replacement and performance or strategy-related factors, such as fund inflow, risk taking and portfolio holding. We also sort the funds into three groups based on their risk-adjusted performance to examine how funds within different ranking groups respond to such interaction. The analysis is constructed on a calendar year basis, so that the probability of managerial replacement in year t-1 is equal to one if the manager leaves the fund in year *t* and no longer appears in our sample.

We first consider the relation between changes in fund inflow and managerial replacement. The estimation model is formulated as follows:

$$
\begin{aligned}
P_{i,t} =& \alpha_i + \beta_i^{(1)} Flow_{i,t-1} + \beta_i^{(2)} (Debt_{i,t-1}/Capital_{i,t-1}) \\
& + \beta_i^{(3)} Age_{i,t-1} + \varepsilon_{i,t}
\end{aligned} \tag{2.7}
$$

where $P_{i,t}$ is the probability of managers being replaced, Flow represents the change of the capital inflow of fund i, it is calculated by Equation 2.5. $Debt/Capital$ is calculated by dividing each fund's long-term debt by its total capitalization and is a measure of the fund's financial leverage, and $Age_{i,t-1}$ is the age of the fund.

Table 2.5 reports estimation results of Equation (2.7). In general, the results in Panel A of the table indicate that the probability of managerial replacement is negatively correlated to the change in fund inflow, and older funds are more likely to dismiss their top managers. Panel A also reports the results based on performance ranking. It is shown that the replacement probability of the funds with higher previous ranking is more sensitive to fund flow changes than is the replacement probability of those with lower ranking. One reason for this may be the asymmetric convex relation between performance and flow changes. Previous research has shown that investors in underperforming funds are 'dead'; in other words, poor performing managers are not penalised accordingly. Moreover, although in general the debt/capital ratio has no explanatory power, in the lower ranking groups the coefficient on this variable is 0.0009 and statistically significant. This indicates that poor performing funds tend to issue more debt to gather more capital for investment.

In Panel B, we include two interactive terms to examine the flow-replacement relation conditional on the debt/capital ratio and fund age, respectively. The estimated coefficients on flow changes are close to the corresponding values in Panel A, but while the flow*dc term is not statistically significant, in Panel A the debt/capital ratio is, indicating that managers' issuing more debt is not conditional on flow changes. In other words, the need to satisfy investors' potential redemption is not necessarily a major motive for poor performing managers to issue debt. Rather, they are likely to seek to increase investment to improve performance by betting on the market. The other interaction term, flow*age, however, is generally statistically significant. In particular, the coefficient on this interaction term is negative for the low ranking group, suggesting that the managerial replacement is more sensitive to flow changes of older funds.

We extend our estimation by including managers' genuine skill status. The results are reported in Panel C. The coefficient on the flow*skill term is negative and statistically significant for the whole sample, which implies that managers with genuine skills are more sensitive to the interaction between flow changes and managerial replacement, particularly in the group of funds with previous higher rankings. The estimated coefficient is -0.5069, while for the similar group in Panel A it is -0.3512. For the funds in the lower ranking group the coefficient is not significant, indicating that fund managers with opposite performance are not penalised equally by flow changes.

Table 2.5 Managerial Replacement and Flow Relation

Dependent Variables	All	Performance Ranking High	Median	Low
Panel A				
Flow	-0.2485***	-0.3512***	-0.4899***	-0.1722
	(0.0000)	(0.0008)	(0.0000)	(0.1338)
dc	0.0019	-0.0012	0.0009	0.0057**
	(0.2185)	(0.5824)	(0.8091)	(0.0179)
Age	0.0010***	-0.0006	0.0054	0.0100***
	(0.0014)	(0.7778)	(0.2155)	(0.0001)
Panel B				
Flow	-0.1602*	-0.3017**	-0.5821***	0.2141
	(0.0836)	(0.0250)	(0.0037)	(0.1200)
Flow*dc	-0.0014	-0.0059	0.0029	0.0119
	(0.6977)	(0.2640)	(0.6150)	(0.1316)
Flow*age	-0.0086**	0.0003	0.0033	-0.0242***
	(0.0124)	(0.9588)	(0.6901)	(0.0000)
Panel C				
Flow*skill	-0.1967**	-0.5069***	-0.0953	0.0117
	(0.0111)	(0.0003)	(0.4756)	(0.9272)
dc*skill	-0.0012	0.0052	-0.0003	-0.0046*
	(0.7511)	(0.1431)	(0.9041)	(0.0922)
age*skill	0.0032	-0.0009	0.0013	0.0068*
	(0.2200)	(0.7725)	(0.7559)	(0.0621)
Observations	5488	1829	1830	1829

Notes: This table reports the estimation from equation (2.7) which can be stated as follows:

$$P_{i,t} = \alpha_i + \beta_i^{(1)} Flow_{i,t-1} + \beta_i^{(2)} (Debt_{i,t-1}/Capital_{i,t-1}) + \beta_i^{(3)} Age_{i,t-1} + \varepsilon_{i,t}$$

We sort all the replaced funds into three groups according to performance ranking in the previous year. Panel A reports the results based on the above model. The results including the effects conditional on flow changes, fund age and managers' genuine skill are reported in Panels B and C, respectively.

2.4.2.3 Managerial replacement-trading strategy relationship

In examining the relation between managers' trading behaviour and managerial replacement, we focus on the influence of portfolio components and the funds' risk exposure on the probability of managerial replacement. We include in the replacement-portfolio holdings analysis the industry concentration index, the proportion of funds' top 10 holdings, the cash to equity ratio and funds' idiosyncratic risk exposure. The baseline model is formulated as:

$$\begin{aligned} P_{i,t} =& \alpha_i + \beta_i^{(1)} ICI_{i,t-1} + \beta_i^{(2)} CE_{i,t-1} + \beta_i^{(3)} RI_{i,t-1} + \beta_i^{(4)} (ICI_{i,t-1} \\ & \cdot Topholdings_{i,t-1}) + \beta_i^{(5)} (RI_{i,t-1} \cdot Topholdings_{i,t-1}) + \varepsilon_{i,t} \end{aligned} \tag{2.8}$$

where ICI stands for the industrial concentration index, *CE* stands for funds' cash to equity holding ratio, RI is the variation of the portfolios' idiosyncratic risk and Topholdings is the value of funds' top 10 holding stocks as a proportion of entire value.

Table 2.6 reports the results. In Panel A, the coefficients on the variable ICI show a mixed influence on managerial replacement. Its effect is not statistically significant in general, but for the funds with previous high ranking the coefficient on ICI is a positive and significant 3.6262, while for funds in the low ranking group the value is -1.9843. It is likely that, taking advantage of specialist knowledge about the market, some fund managers have concentrated their holdings on a certain industrial sector to improve performance, which is also reported in the previous literature (Kacperczyk et al. 2005). It is therefore straightforward to find such a negative relation in the lower ranking group. For the positive coefficient in the higher ranking group, it is likely that managers try to maintain the 'winning' story by manipulating their portfolios to take a higher level of idiosyncratic risk. However, since such superior performance is not a result of genuine stock selection skills, over performing funds with high ICI could also face potential employment risk.

We also examine, via an interaction term, the influence of ICI on managerial replacement conditional on the changes in the funds' top holdings. The results in Panel A indicate that an increase in the funds' top holdings will reduce the negative effect of ICI, particularly for the lower ranking funds. In other words, the investment strategies chosen by the underperforming managers to improve performance would highly deviate from the funds' original objectives, since the coefficient on the interactive term of ICI and Topholdings is positive and statistically significant. Managers tend to decrease their capital in the top 10 equity holdings.

The results for the influence of RI are generally not significantly different from zero, but for the funds in the high ranking group, the coefficient on this variable is -28.5221. Since RI can be considered as an indicator of managers' stock-picking skills, the results suggest that managers with superior performance tend to demonstrate such skills to minimise the employment risk. But the ability to choose the idiosyncratic risk level cannot be considered as a determinant of managerial replacement. Moreover, the effect of RI on the replacement probability through top holding changes has explanatory power only for the high ranking group. There is a negative correlation between RI and managerial replacement, indicating that increasing the portfolios' top 10 holdings will reduce the funds' exposure to idiosyncratic risk, but increase the probability of managers being replaced.

Panel A in this table also reports estimates of the coefficient on the cash/equity ratio and its influence conditional on top holdings. In general, we find that the managers' allocation between cash and equity is negatively related to managerial replacement; i.e. each unit increase in managers' holding of equity will decrease the replacement probability by 2.6913. Such an effect is more significant for funds in the low ranking group since underperforming managers are more likely to increase their investment in equity to bet on the market.

In Panel B of Table 2.6, we include two interactive terms for the examination of the replacement-holding relation conditional on the fund age. For underperforming funds, managers from younger funds are more likely than are managers of older funds to concentrate their holdings on certain sectors. We find a similar outcome in the group of median ranking funds. For the coefficient on RI, the probability of managerial replacement is less sensitive to the idiosyncratic volatility as funds grow old, especially for underperforming funds, which provides managers with an incentive to enlarge their exposure to idiosyncratic risk.

Panel C presents the estimation outcome in relation to the managers' skill status. In general, the coefficients on the cash/equity ratio and idiosyncratic risk are consistent with the estimates reported in Panel 1. It is worth noting that the industry concentration ratio is positively related to the probability of managerial replacement, especially for the managers with genuine stock-picking skills. Although previous literature documents that ICI would act as the indicator of superior performance, the over performance may not persist over time. As shown in Panel C of Table 2.5, skilful managers are not penalised equally in terms of flow changes. Since funds with a high level of ICI are more likely to suffer from market fluctuations, a small amount of capital outflow could trigger managerial replacement. Therefore, it is not recommended for managers in the high ranking fund group to overly concentrate on certain sectors when constructing their portfolios.

In the last two rows of Panel C, we report the interaction between changes in top holding and ICI and RI. Although the signs of the coefficients are the same as in Panel A, it is still worth noting the magnitude of the interplay between RI and changes in top holding. Our results suggest that skilful managers would choose to increase the holdings of certain stocks, leading to possible deviations from the funds' original investment objectives, e.g. stocks with lower idiosyncratic risk or in a particular industrial sector.

Table 2.6 Replacement-Portfolio Holdings Relationship

Dependent Variables	All	Performance Ranking		
		High	Median	Low
Panel A				
ici	-0.2977	3.6262***	-0.8165	-1.9843***
	(0.3862)	(0.0000)	(0.1933)	(0.0014)
ce	-2.6913***	-1.9876***	-2.9786	-3.6087*
	(0.0027)	(0.0242)	(0.1383)	(0.0854)
ri	-0.5576	-28.5221***	2.3621	-0.8542
	(0.8621)	(0.0003)	(0.7013)	(0.8945)
ici*topholding %	3.3293***	-2.3974*	3.8257***	4.7681***
	(0.0001)	(0.0777)	(0.0011)	(0.0004)
ri*topholding %	-7.4174	73.7193***	-15.7599	-15.4525
	(0.5322)	(0.0009)	(0.5214)	(0.4711)
Panel B				
ici	-0.5745	3.8187***	-1.1593*	-2.2686***
	(0.1078)	(0.0000)	(0.0784)	(0.0012)
ce	-2.7136***	-1.9103**	-3.0793	-3.6424
	(0.0046)	(0.0287)	(0.1300)	(0.1142)
ri	3.1802	-33.6390***	9.8314	4.1688
	(0.3732)	(0.0012)	(0.1281)	(0.5890)
ici*topholding %	2.7414***	-2.5174*	3.6222***	3.7876***
	(0.0001)	(0.0721)	(0.0017)	(0.0002)
ri*topholding	-3.0758	76.2266***	-12.6925	-14.0734
	(0.7974)	(0.0015)	(0.5885)	(0.5401)
ici*age	0.0484***	-0.0067	0.0300*	0.1017***
	(0.0002)	(0.6943)	(0.0646)	(0.0000)
ri*age	-0.5374***	0.4000	-0.7169**	-1.0101***
	(0.0023)	(0.1766)	(0.0279)	(0.0065)
Panel C				
ici*skill	0.9474***	3.3472***	-0.0012	-0.7721
	(0.0253)	(0.0001)	(0.9987)	(0.3322)
ce*skill	-2.5222***	-2.2223**	-2.6323	-2.2755
	(0.0284)	(0.0487)	(0.2628)	(0.3676)
ri*skill	-12.1357***	-35.2744***	-7.6999	7.4669
	(0.0212)	(0.0000)	(0.4632)	(0.4074)
ici*topholding*skill	0.4700	-5.2667***	2.4300	4.8073***
	(0.6329)	(0.0000)	(0.2467)	(0.0052)
ri*topholding*skill	15.6585	106.7968***	-0.3353	-64.4758**
	(0.3727)	(0.0003)	(0.9928)	(0.0366)
Observations	5488	1829	1830	1829

Notes: This table reports the results from model (2.8). We sort all the replaced funds into three groups according to performance ranking in the previous year. Panel A reports the results based on the above model while Panel B and C report results including the effects conditional on funds' top holding and managers' genuine skill, respectively.

2.5 Conclusions

We analyse the interplay among fund performance, managerial replacement and portfolio characteristics based on evidence from the UK unit trust market. The study compares the performance shift, risk shift, changes in fund flow and portfolio holdings between the pre- and post-replacement periods. To further test the efficiency of governance mechanism in the UK fund industry, we apply the bootstrapping simulation to separate the managers whose performance is driven by sample variation ('luck') from those with genuine stock selection skills.

Our results indicate that managers' replacement can be predicted by managers' underperformance. Moreover, after comparing managers' actual performance with simulated 'luck'-driven abnormal performance, we show that managers with superior performance that is due to sample variation are more likely to be dismissed by fund management companies in the UK market than are 'unlucky' managers whose inferior performance is generated by 'bad luck'. It suggests that the internal monitor system is effective to identify 'luck' driven managers. However, the probability of substituting managers with genuinely poor skills is quite low compared with the proportion in the sample variation group which indicates that there other factors in addition to the previous year ranking might have more explanation power over the managerial replacement. Furthermore, our analysis of determinants of managers' replacement supports the evidence that the probability of replacement of underperforming managers is less responsive to decreasing fund inflow than is the probability of replacement of outperforming managers. Our results also indicate that changes to portfolios' components, i.e. the adjustment of funds' top holdings, would exert the negative influence on the probability of managers' replacement in those funds with significant inferior previous year's performance.

CHAPTER THREE

FUND FAMILY TOURNAMENT AND PERFORMANCE CONSEQUENCES

3.1 Introduction

Most mutual funds belong to a fund family. Several previous studies examine the characteristics of these fund families. Guedj and Papastaikoudi (2003), and Massa (2003) analyse how performance of the individual fund can be affected by its affiliated family. Nanda, Wang and Zheng (2004) discuss the close relation between the growth of cash inflows of a certain fund and the superior performance of other peer funds within the same family. Gaspar, Massa and Matos (2006) study how a fund family allocates resources to promote the funds which have the potential to improve the profits of the entire fund family. However, previous research devotes little attention to the relation between the behaviour of individual funds and other peer funds within the same family. Kempf and Ruenzi (2008) (KR hereafter) are the first to examine such a connection. They consider the fund tournament phenomenon in the fund family, first reported in Brown, Harlow and Starks (1996). Despite their findings of differential levels of risk exposure for winners and losers, it remains debatable whether the risk taking behaviour stimulated by the fund tournament benefits the fund performance and the overall profits of the fund family. One also wonders whether the risk taking behaviour is a consequence of the agency problem, or just an indication of managers' inferior ability.

Mutual funds alter their risk exposure frequently for various reasons. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a convex relation between the funds' previous performance and changes of their cash inflows. Underperforming funds may therefore take more risks to bet on better performance given the disproportionate response from cash flows to previous fund performance. Underperforming funds may also alter the level of portfolio risk before the reporting date to manipulate their performance record (Goetzmann, Ingersoll, Spiegel and Welch, 2007; Lakonishok, Shleifer, Thaler and Vishny, 1991).

On the other hand, the convex relation between cash flows and performance may not be applicable everywhere. Funds may use risk shifting to indicate active trading or superior stock selection ability, which may not necessarily indent investors' benefits (Kacperczyk, Sialm and Zheng, 2005). Managers are also compelled to work for the interest of the whole family. In the context of a fund family, funds gain resources and information advantages from the family by winning the competition. Also, it is the fund family that decides which managers are to be promoted or demoted based on the tournament outcome. As a result, managers should change their risk exposure only to improve the fund performance, rather than increase the overall uncertainty of the family. However, to date there has been little research on the relation between risk altering and performance shifting.

Tournament is defined as the competition among a group for a fixed prize, and to be rewarded on their relative performance (Conyon, Simon and Sadler, 2001). The tournament phenomenon in fund family has both differences from and similarities to the corporate tournament. The major difference lies in the main concern of these two types of tournament. For most of the corporate tournament literature, it is the reward structure and various efforts made by participants to win the tournament that are of greatest concern (Leonard, 1990; Gibbs, 1993). Given the sound evidence on the compensation scheme, as well as the family strategies to promote top performing funds, the fund tournament literature concentrates more on the efforts made by the managers to win the competition, in which risk altering serves as the major channel.

Another difference between the two types of tournament is the time frame. Corporate tournament can occur at any time with the appearance of the prize(s), or it can be long journey continuing over decades (Rees, 1992), whereas fund tournament literature suggests that fund managers mainly engage in tournament on an annual basis, since the end of year report summarises the managers' averaged performance. Studies also find that risk altering is more popular on a mid-year basis from the managers' perspective (Brown, Harlow and Starks, 1996).

Moreover, traditional corporate tournament concerns competition for employment concerns, for example promotion from vice-president to CEO. The motivation behind such competition is often a rise in pay structure (Rosen, 1986; Bognanno, 2001), since most wage changes are found between jobs rather than within jobs (Lazear, 1992). Fund managers also take employment issues into consideration during portfolio management. But since performance evaluation on managers might be based on a number of criteria, previous research finds that top management replacement is often accompanied by poor observed returns (Khorana, 2001), whereas the fund alphas are more closely related to managers' promotion and demotion (Evans, 2009). Thus, there remains the possibility that top and bottom ranked managers could value the risk taking strategies differently; specifically, underperforming managers will be more concerned with the observed returns as a precaution against being replaced, while top performing ones aim to show their superior ability to pursue rewards.

The common factor behind both types of tournament is the reduced cost of monitoring. Corporate tournament theory suggests that such self-enforcing reward systems are more desirable, compared with monitoring and supervision (Becker and Huselid, 1992). Fund family tournament also carries the characteristic of reducing monitoring cost, as the fund family can benefit from individual managers' stellar performance; in addition, the competition reduces the agency cost, since winning the contest only comes because of performance improvement, which is in line with investors' benefits. However, the existing studies lack empirical evidence to connect the performance consequences of risk taking to family tournament, from both the families' and the investors' perspective.

This research is the first to discuss performance shifting in relation to the risk taking in the family tournament. Using data from the UK unit trust industry, we first examine both the segment and family tournament phenomena in 3 IMA sectors of UK domicile equity funds in the sample period from 2001 to 2010. Our results show that funds with better previous performance actively participate in the family tournaments by increasing their risk exposure in the second half of the calendar year, while the opposite is true in the segment tournament. The results persist when funds are ranked by risk-adjusted performance. But no significant evidence is found to support the existence of the tournament phenomenon when the overall family level of risk is used; i.e., the overall risk exposure of the winning family does not increase in the second half of the year.

We further examine managers' risk taking behaviour under different market condition and our results document a positive relation between family ranks and future risk taking in bear market condition. Namely, mid-year winners increase their risk level higher than the losers since the losing managers are concerned more about their jobs.

Our empirical analysis of the performance consequences show that the interim winners can outperform the losing ones in risk-adjusted returns by taking more risk, whereas the opposite is true when turning to the observed returns. The magnitude of performance differential is the largest when the risk shifting level is low. The decreasing observed returns in the winning group is probably due to the return deteriorations from increased holdings of index-linked stocks. The increasing exposure to the systematic risk of the winning funds from our results supports this finding. Although it seems to be optimal for the mid-year winners to maintain a low level of risk shifting, we argue that winners might value the importance of employment concerns and family favouritism more seriously than the losers. Thus, they aim to signal the fund family of their superior ability by beating the other members with high fund alphas in order to gain more resource from the family. The results from our test of families' cross-fund subsidisation support this view.

We also conduct the performance consequence analysis from the fund family's perspective. We compute the probability of funds being promoted in the segment ranks, which is regarded as the relative performance consequence given the level of risk taking. In general our analysis documents a positive relation between performance ranks of individual funds and their risk taking. The result also suggests that, for a fund family that consists of funds whose performance is extremely poor (dog family), its cross-sectional volatility is positively correlated with the probability of underlying funds being promoted. In other words, dog families are more likely to undertake family strategies by shifting performance or promoting risk taking behaviour across underlying members.

While our findings about the family tournament differ with those in KR, they are consistent with those of Mas-Colell, Whinston and Green (1995). Specifically, the winning funds in a small fund group are more likely to engage in a tournament with strategic interactions. The cut-off points by KR to identify large and small families in the US fund industry are 16, 21, 31 and 36 funds, whereas in the UK the average family size is 4, and the largest family consists of only 11 funds. Thus, our entire sample of fund families can be classified as small families in the KR sense. Second, our results confirm the effects of employment concerns in relation to fund risk taking. Extant research suggests that, despite the compensation schemes that are based on asset values, fund managers are also exposed to employment risk, as they need to keep their jobs. Taking more risk provides a means for the losing managers to bet on better performance, though it may also raise the probability of performing even worse. Relative to the losing managers, the interim winners are under less employment pressure. Therefore, the underperforming managers tend to take less risk than good performers (Chevalier and Ellison, 1997; Kempf, Ruenzi and Thiele, 2009). Third, and most important, our analysis of performance consequences shows that risk taking can serve as an indication of managers' superior stock selection ability. It also acts as a crucial criterion for the fund family to decide which fund should be advertised or favoured with extra resources. Thus, it stands to reason that winner funds would actively consider shifting risk exposure to retain their leading positions. The current research unearths significant empirical evidence of changes in the risk taking behaviour in the family tournaments. Our results also support the conclusion that risk taking helps top performing managers win the competition.

This chapter is organised as follows. The next section summarises the related literature. Section 3.3 describes the empirical methods to be implemented in this research, while section 3.4 discusses the data and presents the descriptive statistics of the datasets. Section 3.5 reports the empirical findings from the tournament analysis, and the performance consequences due to tournament related risk taking. The results are then summarised in the final section.

3.2 Related literature

Our research relates to three strands of literature. First, we revisit the risk shifting phenomenon presented by many fund tournament studies. Brown, Harlow and Starks (1996) (BHS hereafter) are among the first to document the evidence that managers from half-year-losing funds have incentives to alter their risk exposure more significantly than those from the half-year-winning funds. In this seminal research, they report that half-year losers are more likely to increase their exposure to portfolio risk for the second half of the calendar year in an attempt to improve their future position against peer funds, while half-year winners tend to decrease risk exposure to retain their leading position. The motivation behind such tournament behaviour can be explained by the disproportionate amount of capital injected into top performing funds relative to the underperforming funds (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). However, bottom ranked funds might not be equally punished by capital outflows, which encourages the underperforming funds to bet on the market by increasing their risk exposure. Although there is a large body of research related to the tournament behaviour (see for example Koski and Pontiff, 1999; Elton et al., 2003; Huang et al., 2011; Schwarz, 2012), the empirical results are mixed.

Using monthly data and contingent tables, Jans and Otten (2008) find significant evidence that mid-year losers increase risk exposure more than mid-year winners in the first sub period, 1989-1996, of their sample using the UK unit trust data. But the risk shifting behaviour reverses in the rest of their sample period, 1997-2003, as they argue that a strategic game is conducted by both the winners and the losers; i.e., both parties might alter their risk shifting based on the decision made by the opposite parties. Busse (2001) also finds evidence to support the tournament hypothesis; he discovers that fund managers may engage in half-year risk shifting to compete with others from the same investment style, also known as the segment tournament. However, contradictory evidence is found when daily data is applied. Specifically, top performing managers tend to increase their risk exposure more than the bottom performing ones. Similar results are found in Chevalier and Ellison (1997).

In recent research, Kempf et al. (2009) and Schwarz (2011) apply the portfolio holding data in the tournament analysis. They argue that, compared with estimating the realised risk, deploying the portfolio holding data to estimate volatility better represents the managers' intention to alter the exposure to portfolio risk. However, holding data might not be sufficient to address managers' frequent risk shifting, since funds might only publish their holding data on a quarterly basis (or even on a half-year basis).

The second strand of literature relevant to our research is the fund family tournament literature. Fund families play an important role in funds operation. Since individual funds are usually affiliated to different fund complexes, it is the fund family that decides managers' promotion or demotion, and which funds to market (Jain and Wu, 2000). Fund companies also conduct various types of strategies to enhance the performance of certain funds, such as undertaking cross-fund subsidisation to promote funds with high past performance through allocating new IPO shares (Gaspar et al., 2006). On the other hand, fund companies also have the motivation to support family tournament. Nanda et al. (2004) suggest that families with star funds, i.e. funds with top ranking performance against peer funds within the same investment style, attract significantly more new cash inflows than other families. The growing cash inflows can bring new capital not only to the star funds, but also to other funds within the same family, i.e. the spillover effect. They also find evidence that star families tend to increase the volatility of cross-sectional returns in order to increase the odds of creating star funds. In other words, risk taking in family tournament is a reasonable strategy, from which a fund company can benefit greatly.

KR is the first to discuss the tournament behaviour in the context of fund families. They find that the bottom ranked managers in large families tend to increase risk more than top ranked ones, while the opposite occurs in small families. Following the theoretical work by Taylor (2003), KR suggests that there are no strategic interactions in large fund families. Fund managers cannot optimise their decision when too many competitors are present. Therefore, mid-year winners simply choose to reduce risk exposure to retain their positions, without consideration of the strategies played by other mid-year losers. Meanwhile, given the convex reward scheme, bad performance cannot hurt the mid-year losers substantially if they increase their risk exposure.

When the family is small, managers will be concerned about how other competitors behave. Taylor (2003) suggests that in a game with strategic interactions, the mid-year winner will increase their risk exposure to lock their positions, as they are aware of the risk-increasing strategy taken by the losers. With the help of large cash inflows and favouritism from the fund companies, the losers cannot beat the winners when they both undertake the risk-increasing strategy. As a consequence, losers will tend to increase their future risk exposure less than the winners, or maintain it at a more stable level. However, KR also shows a strategic tournament in the group of funds within the same segment, which contradicts the results from prior research, although they argue that the strategic tournament could be time sensitive.

The third strand of literature to which our research is related is the growing field of funds' risk taking. There are a large number of studies discussing the purposes of funds' risk shifting. Most of the studies identify that risk shifting is a major channel for the managers to promote cash inflows. Goetzmann, Ingersoll, Spiegel and Welch (2007) maintain that fund managers can alter the funds' risk exposure with a view to manipulating the performance record. They tend to purchase well-performing stocks and ditch the poor ones immediately before the performance reporting date to attract new cash inflows, a practice known as end-year window dressing (Lakonishok et al., 1991; Musto, 1997). Chevalier and Ellison (1997), and Sirri and Tufano (1998) document a convex shaped relation between fund performance and the change of cash inflows, implying that fund managers can take extra risk for compensation concerns, since underperforming managers are not punished heavily by cash outflows.

In addition to the agency problem, Kacperczyk et al. (2005) suggest that active trading can also be regarded as a sign of managers' superior ability. Thus risk shifting might lead to performance improvement. While much of the research in this field concentrates on searching for the real purposes of funds' risk shifting, some studies focus on whether risk shifting actually benefits the investors. Huang, Sialm and Zhang (2011) (HSZ hereafter) initiate the discussion on the performance consequences of risk shifting. Using portfolio holding data of the US mutual fund industry, they find that funds with stable risk levels provide better performance than funds significantly altering their risk levels. As it is costly for the fund investors to bear the loss of funds during risk shifting, they argue that such behaviour is merely an indication of inferior ability or due to compensation concerns. However, despite a large number of studies examining the tournament behaviour and the risk shifting in the fund industry, few studies have followed the HSZ model to conduct a complete analysis of the performance consequences of family tournament. Our research is therefore set to fill the gap from an empirical perspective.

3.3 Methodology

To identify the risk taking behaviour in the family tournament, we adapt the empirical model suggested by KR, as follows:

$$\begin{aligned}\Delta\sigma_{i,t} =& \alpha_i + \beta_i^{(1)} R_{i,t}^{Fam} D_l + \beta_i^{(2)} R_{i,t}^{Fam} D_s + \beta_i^{(3)} R_{i,t}^{Seg} D_l + \beta_i^{(4)} R_{i,t}^{Seg} D_s \\ &+ \beta_i^{(5)} \sigma_{i,t-1} + \beta_i^{(6)} \Delta\sigma_{med} + \varepsilon_{i,t} \end{aligned} \quad (3.1)$$

where $\Delta_{\sigma_{i,t}}$ is the difference of funds' volatility between the ranking period and the post-ranking period. We use different measures in examining the volatility shifting, including the total risk, the systematic risk and idiosyncratic risk. Volatility difference of the entire family is also calculated, to analyse whether tournament behaviour might occur at the family level. A fund family's overall risk level is based on the value weighted returns of all funds within the same family. Previous studies consider the tournament behaviour on an annual basis, in which the ranking period lasts from 6 to 8 months (e.g. BHS; Jans and Otten, 2008). KR consider only the 7-month ranking period. To fully address the time frame issue of the tournament behaviour, our investigation includes the cases with both the June (6-month ranking period) and July (7-month ranking period) cut-off points, while also considering the quarter-ranking period to further the analysis of managers' risk shifting strategy. In equation (3.1), $R_{i,t}^{Fam}$ and $R_{i,t}^{Seg}$ are the family rank and segment rank, respectively. The segment rank is generated by arranging funds of the same segment in ascending order according to their performance in the ranking period. We classify all funds into three segments according to the IMA category of investment styles, i.e. UK All Companies, UK Equity Income and UK Smaller Companies.

For measuring the performance, BHS and KR use funds' raw returns only, due to the fact that the raw returns are the major concern of investors. Given the recent concern that the close connection between risk and returns might bias the tournament analysis (Schwarz, 2012), we also include the Jensen alphas as a measure of the risk-adjusted performance. In order to make ranks from different investment styles comparable, we normalise the rank by using the function $(R_i - 1)/(N_i - 1)$, where R_i is the segment rank of fund *i* and N_i is the size of the corresponding segment. We calculate the family rank by further ranking the normalised segment rank from funds within the same family in ascending order. Thus, the family rank measures the relative performance of each member in the family. We also normalise the family rank using the same method, with N_i being the size of the corresponding family. $D_l(D_s)$ is the dummy variable that represents a large (small) fund family. We consider two criteria to classify fund family into large and small, namely, the aggregate value of the family and the family size. This is because some of the families may have only a limited number of members, but each member has a large size of underlying assets. The model also includes the funds' volatility in the ranking period, $\sigma_{i,t-1}$, and the median difference of funds' risk in each of the segments, $\Delta\sigma_{med}$, to capture the exogenous factors that lead to risk shifting. The model 3.1 is estimated by using the fixed effect panel regression, as following the results provided by the Hausman test, which compare results given by the fixed effect panel regression and those from the random effect model, supports the validity in using the fixed effect panel regression.

For the performance consequences of family tournament, we apply several analytical tools, including the transition matrix and performance differences, to examine the performance shifting of individual funds. An empirical model is then constructed to analyse how performance changes from the family perspective can be explained by changes in the risk taking behaviour. Given that funds participate in the tournament to win the competition, it is the relative performance rather than the absolute performance that matters to the managers. Thus, we can further link the risk taking behaviour to the rank changes of a certain fund. With the spillover effect and disproportionate relation between historical performance and cash inflows, fund families also have incentives to take on higher risk exposure in family tournament. We thus formulate the empirical model as follows:

$$\begin{aligned}R_{i,t}^{Family} =&\alpha_i + b_i^{(1)} R_{i,t}^{\Delta\sigma} + b_i^{(2)} \Delta\Lambda_{i,t}^{\sigma} D_{Star} + b_i^{(3)} \Delta\Lambda_{i,t}^{\sigma} D_{Dog} + b_i^{(4)} \Delta\Lambda_{i,t}^{\sigma} D_{Star,Dog} \\ &+ b_i^{(5)} \Delta\Lambda_{i,t}^{\beta} D_{Star} + b_i^{(6)} \Delta\Lambda_{i,t}^{\beta} D_{Dog} + b_i^{(7)} \Delta\Lambda_{i,t}^{\beta} D_{Star,Dog} \\ &+ b_i^{(8)} \Delta\Lambda_{i,t}^{\varepsilon} D_{Star} + b_i^{(9)} \Delta\Lambda_{i,t}^{\varepsilon} D_{Dog} \\ &+ b_i^{(10)} \Delta\Lambda_{i,t}^{\varepsilon} D_{Star,Dog} + \varepsilon_{i,t} \end{aligned} \tag{3.2}$$

where $R_{i,t}^{Family}$ is now the overall family rank of family *i* in the post-ranking period. The family rank is worked out by first taking the difference in the segment rank of each sampled fund between the ranking and post-ranking period. Then we further rank each of the fund families using the aggregate ranking ratio. For example, if family *i* has three funds, A, B and C the differences in normalised segment rank for each fund are $A = 0.1; B = 0; C = -0.3$. Here, $A = 0.1$ means that fund A improves its ranking ratio by 0.1; fund C has been demoted by 0.3 in the segment rank and fund B has no change in its rank. The aggregate ranking ratio for family *i* thus equals $-0.3 + 0 + 0.1 = -0.2$. All the families in our sample are then ranked according to this ratio. A high $R_{i,t}^{Family}$ indicates that the funds within the family experience a positive performance shift with a smaller cost of funds being demoted. $R_{i,t}^{\Delta\sigma}$ measures the level of risk shifting in a certain family. A similar aggregate ranking ratio is generated for each family according to the changes in the level of risk exposure of the underlying funds. $\Delta\Lambda_i^{\sigma}$, $\Delta\Lambda_i^{\beta}$ and $\Delta\Lambda_i^{\varepsilon}$ measure the cross-sectional differences in the total risk, systematic risk and idiosyncratic risk, respectively. D_{Star} is equal to 1(0), if the family that fund *i* is affiliated to is a star (dog) family. A star family contains at least one fund ranked in the top quartile of the segment (star fund) in the ranking period, while a dog family includes any bottom performing funds (dog fund). $D_{Star,Dog}$ denotes a family that has both star and dog funds in the ranking period. Both star and dog families may have motivation to promote family tournament; i.e. the dog family will seek to improve the performance of its dog fund by betting on the market, while the star family tends to retain the position of the star funds in its group. Further, fund families also have the ability to promote the tournament behaviour by resource reallocation, i.e. family favouritism and the spillover effect. Thus, by sorting families into star and dog types, we are able to explore which types of families are more likely to be involved in the tournament. Additionally, we may discover how performance of the peer funds in a star/dog family responds to the tournament behaviour.

3.4 Data

The funds' raw data are obtained from Morningstar. We collect daily total returns data for the UK unit trust industry during the period between 2001 and 2010. The funds selected into the sample are all UK domiciled, equity based unit trusts and OEICs.[4] We exclude funds targeting fixed income securities and mixed investments; the index linked funds are also taken out of the sample. The sampled funds belong to 3 IMA sectors: UK All Companies, UK Equity Income and UK Small Companies. We treat these 3 IMA sectors as the 3 largest segments in our tournament analysis. With regard to fund families, this research regards a fund family as being formed by the funds that are managed by the same fund company. For each of the families, we only keep the oldest fund in the same share class, since funds within the same share class deliver similar rates of returns.[5]

Table 3.1 reports the summary statistics for the sample funds in this research. It shows a rapid growth of the UK fund industry, although the population of UK funds is still moderate in numbers compared to the US fund industry. Both the number of funds and the number of fund families increased dramatically in the sample period. There were only 159 UK domiciled equity funds in 2001, and this number had doubled to 324 by 2010. Columns 2 and 3 report the mean cross-sectional returns and standard deviations of the sample funds. In general, we see a weak association between higher levels of risk and higher observed returns

[4] Unit trusts and OEIC s are both open-ended investments with different bid/ask pricing, legal structures and up-front loads. However in practice, they can both be regarded as mutual fund equivalents.

[5] The oldest fund is normally the first fund established by the fund company in the share class. Other peer funds within the same share class can be created individually or by splitting from the oldest one, but they all share a management team and a similar portfolio composition. Morningstar provides additional information indicating the oldest fund from the same share class.

among the fund population, but exceptions occur in 2001/2002 and 2007/2008, when the market suffered from the dot-com bubble and the global financial crisis.

Table 3.1 Summary statistics

Year	Mean return (%)	Mean S.D. (%)	No. of funds	No. of fund families
2001	-0.0474	1.1713	159	41
2002	-0.1123	1.1756	172	41
2003	0.0916	0.9087	189	44
2004	0.0500	0.5743	210	50
2005	0.0777	0.5857	225	52
2006	0.0676	0.7063	250	56
2007	-0.0032	0.9412	277	60
2008	-0.1731	1.8427	294	62
2009	0.1187	1.2443	302	63
2010	0.0713	0.9379	324	65

Notes: This table shows the summary statistics for the sample UK equity funds considered by this study. Columns 2 and 3 present the mean sum of total daily returns and mean sum of standard deviations of all sample funds, respectively. Column 4 presents the total number of funds in the sample. In Column 5, the number of fund families for each year in the sample is shown.

Apart from the raw returns, we also estimate the Jensen alphas as a measure of the funds' risk-adjusted performance. We employ three sets of benchmark returns to proxy the excessive market returns (MKT), the size effect (SMB), the book to market effect (HML) and the momentum effect (UMD). We choose the FTSE All Shares index as the basis for calculating market returns, and hence the MKT. Use of the MKT factor is motivated by the conventional CAPM model. The HML and SMB factors are adopted following the Fama-French 3-factor model, and computed by two pairs of market portfolios. SMB is generated by taking the difference between the FTSE 100 index and the FTSE small capital index; HML is calculated by taking the difference between the MSCI UK Growth index and MSCI

UK Value index suggested by Cuthbertson et al. (2008). Following the method presented in French's website, the UMD factor in the Carhart 4-factor model is generated by extracting the returns of the 1-year low return portfolio from the returns of the 1-year high return portfolio.

3.5 Empirical results

3.5.1 Risk taking in the segment and family tournaments

Table 3.2 reports the regression results fitting by model (3.1). In general, it shows significant evidence of funds engaging in both family and segment tournaments. In column 2 of Panel A, when the half-year ranking period is considered, the main indicator of family tournament, $R_{i,t}^{Fam}$, has a significant and positive coefficient on the large-value-family dummy, although no significant tournament behaviour is found in small families. The segment tournament indicator, $R_{i,t}^{Seg}$, has a significantly negative factor loading on either the large or the small family dummy variable. The positive coefficient on $R_{i,t}^{Fam} \cdot D_l^V$ indicates that top ranking funds in the large families take more risk than bottom ranked ones, which is consistent with the theoretical prediction of strategic tournament by Taylor (2003). This result is also consistent when the cut-off point of the ranking period turns to be 7 months in the second column of Panel A.

The negative coefficient on $R_{i,t}^{Seg}$ suggests a non-strategic segment tournament in which half-year underperforming funds are more likely to increase their risk exposure in the second half of the year than are the top performing ones. The risk shifting behaviour in segment tournament is more sensitive in small families than in large ones by more than 50 basis points.

Our findings regarding the family tournament are contrary to those reported in KR, which suggests that underperforming funds within a small family increase risk more than over-performing ones. Our results however do indicate that managers of the mid-year winners choose to increase their risk exposure than the mid-year losers. This is particularly true for those from the large sized families, since large sized funds have more capital to fund strategy shifting or are the market makers that enjoy some competitive edge over the small funds.

Chevalier and Ellison (1997) argue that top performing managers may increase their risk level to retain their leading positions. In the segment tournament, mid-year winners are less motivated to compete with peer funds within the same segments, as the only reward for the winner is the new cash inflows. Existing research however shows no supportive evidence of performance improvement over the peer losers after the risk shifting, implying that it actually becomes even harder to attract new cash inflows by increasing risk exposure (see for example HSZ).

Mid-year winners are highly motivated in the family tournament since the winner of the tournament may be rewarded by the fund company through various forms of family favouritism. Even those mid-year winners who have already been rewarded by the family may seek for continuation of such favouritism (Guedj and Papstaikoudi, 2003; Nanda et al., 2004 and Gaspar et al., 2006). Large sized families may also encourage their member funds, particularly the winning ones, to participate in the tournament, since the winner funds could spare their new capital to benefit the other peer funds in the family. Compared with large sized families, smaller ones have no competitive edge in shifting investment strategies. Columns 4-6 of Panel A in Table 3.2 report the outcome of the research that is extended to include the tournament analysis on a quarterly basis. The family tournament behaviour is consistently significant throughout the quarterly analysis, while segment tournament behaviour disappears between the first and second quarter.

In Panel B of Table 3.2, the fund families are classified into large or small according to the number of their underlying family members. We find that the results in general agree with those given in Panel A. Funds in small sized families are not actively involved in family tournament. An additional reason for this could be that funds in the families with fewer members are normally managed by the same manager or have a similar portfolio composition, which leads them to be even less motivated to engage in a family tournament.

To further analyse family tournaments we re-rank the funds according to their risk-adjusted returns in the ranking period, since the previous literature suggests that a close relation between risk and returns could jeopardise the tournament analysis. The risk-adjusted returns can be estimated by using the Carhart 4 factor model,

$$R_{i,t} = \alpha_i + \beta_i MKT_t + \beta_i^{HML} HML_t + \beta_i^{SMB} SMB_t + \beta_i^{UMD} UMD_t + \varepsilon_{i,t}$$

where α_i is the Jensen alpha measuring the risk-adjusted returns of fund *i*, MKT_t is the excess market return; HML_t is the return from the book to market portfolio; SMB_t stands for the return from the size portfolio and UMD_t is the return from the momentum portfolio.

Table 3.2 Family and segment tournaments (Raw Returns)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^V$	0.0050**	0.0049**	0.0040**	0.0045**	0.0065**
$R_{i,t}^{Fam} \cdot D_s^V$	0.0033	0.0018***	0.0020	-0.0019	0.0040
$R_{i,t}^{Seg} \cdot D_l^V$	-0.0076***	-0.0068***	0.0037	-0.0104***	-0.0076**
$R_{i,t}^{Seg} \cdot D_s^V$	-0.0127***	-0.0074***	0.00002	-0.0091***	-0.0111***
$\sigma_{i,t-1}$	-3.5697***	-2.9213***	-4.8218***	-4.0134***	-3.6620***
$\Delta\sigma_{med}$	13.6588***	12.9068***	7.0209***	14.3347***	11.8634***
R^2	88.35%	89.12%	74.18%	86.61%	83.15%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_l^S$	0.0054**	0.0034	0.0076***	0.0031	0.0067**
$R_{i,t}^{Fam} \cdot D_s^S$	0.0028	0.0033	0.0023	0.0003	0.0041
$R_{i,t}^{Seg} \cdot D_l^S$	-0.0105***	-0.0061**	-0.0007	-0.0091***	-0.0097***
$R_{i,t}^{Seg} \cdot D_s^S$	-0.0115***	-0.0098***	0.0036	-0.0111***	-0.0095***
$\sigma_{i,t-1}$	-3.5662****	-2.9171***	-4.8229***	-4.0229***	-3.6757***
$\Delta\sigma_{med}$	13.6754***	12.9184***	7.0462***	14.3398***	11.8655***
R^2	88.34%	89.13%	74.23%	86.58%	83.12%

Notes: This table presents the regression results from the family tournament model (3.1). $R_{i,t}^{Fam}$ and $R_{i,t}^{Seg}$ are the family and segment ranks based on the funds' daily total returns, respectively. D_l (D_s) is the dummy variable which equals to 1(0) when fund *i* belongs to a large (small) fund family. $\sigma_{i,t-1}$ indicates the risk level that fund *i* is exposed to in the ranking period and $\Delta\sigma_{med}$ is the median difference of the segment volatility. Funds' daily returns from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Panel A reports the results when fund families are sorted by funds' aggregate market size, while in Panel B results are sorted by the number of funds in a family. Column 1 presents the results when 6 months is taken as the ranking period and column 2 shows the results when the ranking period is 7 months and post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.3 reports the results from model (3.1) based on using the Jensen alpha from the Carhart 4 factor model as the ranking criterion. We find similar tournament behaviour in the large sized families, where $R_{i,t}^{Fam} \cdot D_l^V$ is found to have a significant and positive loading. Its parameter value as shown in Table 3.3 is very close to that of the coefficients on $R_{i,t}^{Fam} \cdot D_l^V$ in Panel A of Table 3.2, with only an 8-basis-point difference. Funds within small sized families are not found to increase their risk exposure significantly. Therefore, our analysis indicates a pervasive phenomenon of family tournament among large sized fund families. However, evidence reported in Table 3.3 does not support the segment tournament in both large and small families, as none of the coefficients on $R_{i,t}^{Seg}$ are significantly different from 0.

Employment concern is another incentive that can trigger managers' risk altering. Kempf et al. (2009) find that managers change their risk level differently during distinct market condition. They argue that mid-year winners increase their risk exposure more than the mid-year losers in bear market since the losing managers are more concerned about their jobs (employment incentive dominant). Opposite situation occurs in bull market when compensation is the major concern among the managers (compensation incentive dominant). To further test the distinguishing risk shifting during these two types of market condition, we apply the empirical model suggested by Kempf et al. (2009). The model is described as following:

$$\Delta\sigma_{i,t} = \alpha_i + \beta_i^{(1)} R_{i,t}^{Fam} D^{Com} + \beta_i^{(2)} R_{i,t}^{Fam} D^{Emp} + \varepsilon_{i,t} \tag{3.3}$$

where $R_{i,t}^{Fam}$, the fund's family rank, is interacted with the dummy variable which classify the market condition into bear and bull.[6] Table 3.4 reports the results.

[6] We adopt the method suggested by Kempf et al. (2009) to classify the sampled years into bear and bull ones. Thus, 2003, 2005, 2006, 2009 and 2010 is considered as bull years (compensation incentive dominant)

Table 3.3 Family and segment tournaments (4 Factor Model Alpha)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^V$	0.0058**	0.0049**	0.0029	0.004*	0.0037
$R_{i,t}^{Fam} \cdot D_s^V$	0.0022	0.002	0.0053***	-0.0013	0.0048**
$R_{i,t}^{Seg} \cdot D_l^V$	0.0005	0.0028	-0.0017	0.0016	-0.0059**
$R_{i,t}^{Seg} \cdot D_s^V$	-0.002	0.0026	-0.0069***	-0.0011	-0.0091***
$\sigma_{i,t-1}$	-3.5048***	-2.9170***	-4.8114***	-3.8839***	-3.6208***
$\Delta\sigma_{med}$	13.6334***	12.8792***	7.05774***	14.2787***	11.8891***
R^2	88.32%	89.11%	74.22%	86.61%	83.28%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_l^S$	0.0047**	0.0048**	0.0056**	0.0028	0.0056**
$R_{i,t}^{Fam} \cdot D_s^S$	0.0034	0.0025	0.0028	-0.0001	0.0031
$R_{i,t}^{Seg} \cdot D_l^S$	-0.0007	0.0026	-0.0053**	0.0002	-0.0073**
$R_{i,t}^{Seg} \cdot D_s^S$	-0.0027	0.0017	-0.0038	-0.0014	-0.0084***
$\sigma_{i,t-1}$	-3.5000***	-2.9157***	-4.8138***	-3.8892***	-3.6295***
$\Delta\sigma_{med}$	13.6676***	12.8787***	6.9834***	14.3356***	11.8775***
R^2	88.32%	83.71%	74.06%	86.55%	83.24%

Notes: This table presents the regression results from the family tournament model (3.1). $R_{i,t}^{Fam}$ and $R_{i,t}^{Seg}$ are the family and segment ranks respectively based on funds' alphas estimated by the Carhart 4 factors model. D_l (D_s) is the dummy variable which equals to 1(0) when fund *i* belongs to a large (small) fund family. $\sigma_{i,t-1}$ is the risk level that fund *i* is exposed to in the ranking period and $\Delta\sigma_{med}$ is the median difference of the segment volatility. Funds' daily returns from 3 UK IMA segments, UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Panel A reports the results when the fund families are sorted by funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results for the 6-month ranking period and column 2 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Our results show significantly distinct risk shifting between the bear and bull market. Mid-year winners are more likely to increase their risk exposure than the

while the rest of the sampled years are in bear condition (employment incentive dominant).

mid-year losers when the employment incentive is dominant in that year, whereas the opposite is true when the compensation incentive is dominant in the sampled year. For example, the coefficient is 6.79% for $R_{i,t}^{Fam} \cdot D^{Emp}$ and -4.92% for $R_{i,t}^{Fam} \cdot D^{Emp}$ when 6-month ranking period is considered. Also, it seemed that the employment incentive is more sensitive with the risk shifting than the compensation incentive given the coefficient of $R_{i,t}^{Fam} \cdot D^{Emp}$ is larger in absolute value. Column 3 of Table 3.4 reports similar results as those shown in the previous column.

The findings in Table 3.4 further confirm our concerns regarding to the risk taking driven by employment incentive. Increasing risk exposure also adds more uncertainties to the holding portfolio, which may lead to even worse performance in the future. Since underperforming managers are under more employment pressures, they are more cautions with risk taking than the over performing ones. Meanwhile, the higher sensitivity between the risk shifting and employment concerns is also consistent with our overall finding on the relation between risk taking and fund previous performance in Table 3.2, where interim winners tend to increase their level of risk more than the loser for all sampled years.

Table 3.4 Employment and compensation driven risk taking

Risk taking	(6, 6)	(7, 5)
$R_{i,t}^{Fam} \cdot D^{Emp}$	0.0679***	0.0668***
	(4.2426)	(4.4548)
$R_{i,t}^{Fam} \cdot D^{Com}$	-0.0492***	-0.0577***
	(-3.2526)	(-4.0921)
R^2	61.11%	55.29%

Notes: This table presents the regression results from the family tournament model (3.3). $R_{i,t}^{Fam}$ is the family ranks based on funds' observed mean returns. D^{Com} (D^{Emp}) is the dummy variable which equals to 1 when the sampled year is compensation (employment) incentive dominant. We classify the market into bull (bear) when the mid-year return of the FTSE All Share Index is positive (negative). Funds' daily returns from 3 UK IMA segments, UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Column 2 presents the results for the 6-month ranking period and column 3 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

We extend our analysis to look at the tournament behaviour on the family basis. Fund families are ranked according to their mean value weighted returns in the ranking period and we create dummy variables indicating a star (dog) family when it has at least one top performing (bottom performing) fund. The empirical model is formulated as follows:

$$\begin{aligned}\Delta\sigma_{i,t}^{Family} =& \beta_i^{(1)} R_{i,t}^{Family} D_l^V + \beta_i^{(2)} R_{i,t}^{Family} D_s^V + \beta_i^{(3)} D_{Star} \\ &+ \beta_i^{(4)} D_{Dog} + \beta_i^{(5)} D_{Star,Dog} + \beta_i^{(7)} \sigma_{i,t}\end{aligned} \tag{3.4}$$

where the risk shifting of the whole family is computed by taking the difference of volatility of families' value weighted returns between the ranking and post-ranking periods.

Table 3.5 reports the regression results from model (3.4). The coefficients on $R_{i,t}^{Family} \cdot D_l^V$ and $R_{i,t}^{Family} \cdot D_s^V$ are not significant, indicating that fund families do not participate in the tournament by altering their overall risk level. Both Tables 3.2 and 3.3 show a distinct difference in risk taking behaviour between winners and losers within the same family, which can offset the risk level taken by their affiliated family. For the small families, those with fewer members are normally under the management of the same team, and with similar investment strategies would be less active in participating in tournament. Furthermore, both D_{Star} and $D_{Star,Dog}$ have significant coefficients in the (6, 6) interval of Panel A, with 13 and 19 basis points, suggesting that funds within the star families tend to take more risks. This is consistent with our previous findings, in which top performing funds increase their risks more than bottom performing ones. Particularly, since star families contain funds ranked in the top 10% of the corresponding segment, the results given in Table 3.5 imply that the increase of the families' overall risk is mainly attributable to the risk shifting undertaken by the star funds, while the other peer funds, especially the dog funds, maintain stable risk levels. This finding can also be explained as the direct consequence of family subsidisation, since fund companies can keep star funds informed with more valuable information in order to utilise the spillover effect.

Table 3.5 Whole family tournaments

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^V$	0.0004	-0.0005	-0.0005	0.0010	-0.0015*
$R_{i,t}^{Fam} \cdot D_s^V$	0.0006	-0.0002	-0.0005	0.0009	-0.0012
D_{Star}	0.0013***	0.0007	0.0011	0.0014**	-0.0001
D_{Dog}	0.0008	-0.0003	-0.0001	0.0014**	-0.0003
$D_{Star,Dog}$	0.0019***	0.0014***	0.0004	0.0015**	-0.0002
$\sigma_{i,t-1}$	-15.497***	-15.0568***	-7.8053***	-13.5333***	-10.3831***
R^2	77.44%	65.35%	49.01%	53.19%	26.75%
Panel B	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^S$	0.0006	-0.0003	-0.0004	0.0013	-0.0011
$R_{i,t}^{Fam} \cdot D_s^S$	0.0004	-0.0003	-0.0006	0.0007	-0.0016*
D_{Star}	0.0013***	0.0007	0.0011	0.0013*	-0.0001
D_{Dog}	0.0007	-0.0003	-0.0001	0.0013**	-0.0004
$D_{Star,Dog}$	0.0018***	0.0013**	0.0003	0.0013**	-0.0003
$\sigma_{i,t-1}$	-15.468***	-15.0265***	-7.7978***	-13.4907***	-10.3292***
R^2	77.48%	65.34%	49.00%	53.30%	26.96%

Notes: This table presents the regression results on risk shifting in the family tournament. $R_{i,t}^{Fam}$ is the rank of the family return, which is calculated by using the value weighted return of funds within the same family. D_l (D_s) is the dummy variable, which equals to 1(0) when family *i* is a large (small) fund family. D_{Star} (D_{Dog}) equals to 1(0) when family *i* is a star (dog) family. $\sigma_{i,t-1}$ is the risk of family i in the ranking period. Funds' daily returns from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Panel A reports the results when fund families are sorted by the funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results where 6 months is the cut-off point for a ranking period and column 2 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

3.5.2 Risk characteristics in segment and family tournaments

We now extend our investigation to deploy alternative risk measures in analysing the tournament behaviour. Tables 3.6 and 3.7 report results when the market beta and the idiosyncratic risk are used to compute the level of risk shifting.

In Tables 3.6 and 3.7, the statistical significance of coefficients on $R_{i,t}^{Fam} \cdot D_l^V$ in both the (6, 6) and (7, 5) intervals of Panel A suggests that leading managers of the family increase more of their systematic risk in the tournament than do the losing ones. This result is further enhanced in Panel B when families are sorted according to the number of their underlying funds, i.e. with a parameter value of 6.23% and 7.88% respectively for the (6, 6) and (7, 5) intervals. The outcome implies that top performing managers increase their market beta by holding more equities in the benchmark index to time the market. While cross subsidisation can bring more resources to finance major strategy changes by the winning funds, it seems reasonable for the winning funds to decrease uncertainty resulting from holding small value equities, since previous evidence suggests that in general the index-linked funds outperform the actively managed funds. The results in Panels A and B of Table 3.7 also confirm this finding by showing no statistically significant evidence of family tournament when the idiosyncratic risk is considered.

Compared with family tournaments, in Table 3.6 no evidence is found to support the shifts in risk taking behaviour in terms of systematic risk in the segment tournament. However, the losing funds are found to increase their idiosyncratic risk exposure more than the winning funds in the second half of the calendar year, as shown in Table 3.6, where $R_{i,t}^{Seg} \cdot D_l$ has the coefficient of -6.1% and -8.4% in Panel A and Panel B, respectively. This result remains significant in the small family case. HSZ find similar results in their research. They hold that underperforming funds tend to take more idiosyncratic risks by increasing portfolio concentration or changing stock selection. But such an effort brings no positive feedback to performance consequences. Similar arguments can be found in Ang, Hodrick, Xing and Zhang (2006), for example. Given disproportionate responses of the growing cash inflows, it comes as no surprise to see that losing funds choose to increase their exposure to uncertainty surrounding their portfolio with a view to improving performance in the segment tournament.

Tables 3.8 and 3.9 present the regression results from model (3.3) when families' overall systematic risk and idiosyncratic risk are used to compute the risk level. For most of the sample intervals, no significant evidence on risk taking is found regarding the family and segment tournaments. However, the last columns of Tables 3.8 and 3.9 suggest that low-ranked fund families take more overall systematic and idiosyncratic risks in the tournament during the final quarter of the calendar year. It is plausible that the results from the end-year window dressing behaviour when underperforming funds devote every effort to promoting their performance before the reporting date.

Table 3.6 Family and segment tournaments (Market Beta)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^V$	0.0363*	0.0497***	0.0484***	0.0180	0.0408***
$R_{i,t}^{Fam} \cdot D_s^V$	0.0209	0.0448**	0.0156	-0.0049	0.0572***
$R_{i,t}^{Seg} \cdot D_l^V$	-0.0137	0.0035	-0.0524***	0.0470**	-0.0193
$R_{i,t}^{Seg} \cdot D_s^V$	-0.0471**	-0.0303	-0.0455**	0.0113	-0.0578***
$\beta_{i,t-1}$	-2.3525***	-3.4309***	-0.2903***	-0.1070***	-0.3457***
$\Delta\beta_{med}$	12.3390***	11.8658***	0.5272***	0.8219***	0.4662***
R^2	44.12%	38.27%	65.64%	41.17%	59.19%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_l^S$	0.0623***	0.0788***	0.0781***	0.0338**	0.0782***
$R_{i,t}^{Fam} \cdot D_s^S$	-0.00236	0.0202	-0.0051	-0.0183	0.0243*
$R_{i,t}^{Seg} \cdot D_l^S$	-0.0569**	-0.0396*	-0.0909***	0.0127	-0.0704***
$R_{i,t}^{Seg} \cdot D_s^S$	-0.0136	0.0051	-0.0159	0.0381**	-0.0053
$\beta_{i,t-1}$	-2.3124***	-3.4064***	-0.2902***	-0.1031***	-0.3456***
$\Delta\beta_{med}$	12.3586***	11.8913***	0.5345***	0.8244***	0.4699***
R^2	44.25%	38.31%	65.88%	41.01%	59.08%

Notes: This table presents the regression results from model (3.1) where $\Delta\sigma_{i,t}$ is given by the difference of the market beta between the ranking and post-ranking periods. The market beta is estimated by the Carhart 4 factors model. $R_{i,t}^{Fam}$ and $R_{i,t}^{Seg}$ are the family and segment ranks based on funds' daily returns. D_l (D_s) is the dummy variable which equals to 1(0) when fund *i* belongs to a large (small) fund family. $\beta_{i,t-1}$ is the market beta of fund *i* in the ranking period and $\Delta\beta_{med}$ is the median difference of the segment beta. Funds' daily returns in the sample period of 2001 to 2010 from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are used to estimate the market beta. Panel A reports the results when fund families are sorted by funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results where 6 months is taken as the cut-off point for the ranking period and column 2 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.7 Family and segment tournaments (Idiosyncratic Risk)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_l^V$	0.0035	0.0026	-0.0004	0.0036	0.0035
$R_{i,t}^{Fam} \cdot D_s^V$	0.0024	0.0012	0.0004	0.0007	0.0050**
$R_{i,t}^{Seg} \cdot D_l^V$	-0.0061***	-0.0036	0.0031	-0.0054**	-0.0064**
$R_{i,t}^{Seg} \cdot D_s^V$	-0.0089***	-0.0051**	0.0004	-0.0050**	-0.0075***
$\sigma_{\varepsilon i,t-1}$	-3.5591***	-3.1808	-4.5610***	-3.9013***	-3.6651***
$\Delta\sigma_{\varepsilon_{med}}$	12.5259***	11.5825	5.1820***	13.7519***	10.4571***
R^2	78.89%	79.10%	40.31%	72.76%	73.44%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_l^S$	0.0036	0.0003	0.0008	0.0019	0.0035
$R_{i,t}^{Fam} \cdot D_s^S$	0.0022	0.0031	-0.006	0.0022	0.0049**
$R_{i,t}^{Seg} \cdot D_l^S$	-0.0084***	-0.0028	0.0015	-0.0051**	-0.0049*
$R_{i,t}^{Seg} \cdot D_s^S$	-0.0072***	-0.0067**	0.0012	-0.0053**	-0.0095***
$\sigma_{\varepsilon i,t-1}$	-3.5715***	-3.1907***	-4.5775***	-3.9056***	-3.6625***
$\Delta\sigma_{\varepsilon_{med}}$	12.5394***	11.6465***	5.1838***	13.7525***	10.4791***
R^2	78.86%	79.12%	40.24%	72.74%	73.48%

Notes: This table presents the regression results from model (3.1) where $\Delta\sigma_{i,t}$ is given by the difference of the idiosyncratic risk between the ranking and post-ranking periods. The idiosyncratic risk is proxied by the standard deviation of the error term from the Carhart 4 factors model. $R_{i,t}^{Fam}$ and $R_{i,t}^{Seg}$ are the family and segment ranks based on funds' daily returns. D_{large} (D_{small}) is the dummy variable which equals to 1(0) when fund *i* belongs to a large (small) fund family. $\sigma^2_{\varepsilon}{}_{i,t-1}$ is the market beta of fund *i* in the ranking period and $\Delta\sigma_{\varepsilon_{med}}$ is the median difference of the segment beta. Funds' daily returns in the sample period of 2001 to 2010 from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are used to estimate the market beta. Panel A reports the results when fund families are sorted by funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results when the cut-off point for the ranking period is 6 months, and column 2 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is present. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.8 Family and segment tournaments (Family Beta)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_{large}^{V}$	-0.0005	-0.0110	-0.0095	-0.0234	-0.0418***
$R_{i,t}^{Fam} \cdot D_{small}^{V}$	-0.0012	-0.0119	-0.0059	-0.0183	-0.0420***
D_{Star}	-0.0129	-0.0084	0.0234	0.0065	0.0065
D_{Dog}	-0.0111	-0.0102	0.0132	0.0004	-0.0155
$D_{Star,Dog}$	-0.0036	0.0079	0.0266*	0.0177	0.0182
$\beta_{i,t-1}$	-0.2860***	-0.3764***	-0.4786***	-0.3069***	-0.5037***
R^2	11.86%	26.42%	38.84%	11.13%	48.89%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_{large}^{S}$	-0.0078	-0.0111	-0.0173	-0.0435*	-0.0363**
$R_{i,t}^{Fam} \cdot D_{small}^{S}$	0.0060	-0.0119	0.0042	-0.0067	-0.0462**
D_{Star}	-0.0118	-0.0084	0.0242	0.0109	0.0060
D_{Dog}	-0.0090	-0.0102	0.0167	0.0045	-0.0171
$D_{Star,Dog}$	0.0002	0.0078	0.0322**	0.0273	0.0158
$\beta_{i,t-1}$	-0.2885***	-0.3764***	-0.4786***	-0.3091***	-0.5030***
R^2	11.93%	26.42%	39.05%	14.01%	48.88%

Notes: This table presents the regression results from model (3.4) where $\Delta\sigma_{i,t}$ is given by the difference of the family's market beta between the ranking and post-ranking periods. The market beta is estimated by the Carhart 4 factors model. $R_{i,t}^{Fam}$ is the returns rank of the entire fund family. The family returns are calculated by using the value weighted returns of the funds within the same family. D_{large} (D_{small}) is the dummy variable which equals to 1(0) when family i is a large (small) fund family. D_{Star} (D_{Dog}) equals to 1(0) when family i is a star (dog) family. $\beta_{i,t-1}$ is the market beta of family i in the ranking period. Funds' daily returns from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Panel A reports the results when fund families are sorted by funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results when the cut-off point for the ranking period is 6 months, and column 2 shows the results when the ranking period is 7 months and post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.9 Family and segment tournaments (Family Idiosyncratic Risk)

Panel A	(6, 6)	(7, 5)	(Q1,Q2)	(Q2,Q3)	(Q3,Q4)
$R_{i,t}^{Fam} \cdot D_{large}^{V}$	0.0022	-0.0017	0.0002	0.0048*	-0.0125***
$R_{i,t}^{Fam} \cdot D_{small}^{V}$	0.0024	0.0005	-0.0009	0.0019	-0.0092***
D_{Star}	-0.0006	0.0023	0.0002	-0.0020	-0.0004
D_{Dog}	-0.0001	0.0015	-0.0015	0.0005	-0.0018
$D_{Star,Dog}$	0.0012	0.0043**	0.0019	0.0001	0.0011
$\sigma_{\varepsilon i,t-1}$	-6.0783***	-5.3604***	-5.8952***	-6.0422***	-5.4827***
R^2	13.78%	9.79%	24.82%	14.18%	9.29%
Panel B	**(6, 6)**	**(7, 5)**	**(Q1,Q2)**	**(Q2,Q3)**	**(Q3,Q4)**
$R_{i,t}^{Fam} \cdot D_{large}^{S}$	0.0028	-0.0005	-0.0002	0.0055*	-0.0103***
$R_{i,t}^{Fam} \cdot D_{small}^{S}$	0.0018	-0.0003	-0.0007	0.0017	-0.0118***
D_{Star}	-0.0007	0.0022	0.0002	-0.0022	-0.0004
D_{Dog}	-0.0003	0.0014	-0.0015	0.0003	-0.0024
$D_{Star,Dog}$	0.0009	0.0039**	0.0019	-0.0004	0.0004
$\sigma_{\varepsilon i,t-1}$	-6.0983***	-5.3162***	-5.9292***	-6.1744***	-5.5457***
R^2	13.90%	9.77%	24.82%	14.28%	9.38%

Notes: This table presents the regression results from the family tournament analysis model (3.4), where $\Delta\sigma_{i,t}$ is given by the difference of the family's idiosyncratic risk estimated by the standard deviation of the error term from the Carhart 4 factors model between the ranking and post-ranking periods. $R_{i,t}^{Fam}$ is the return rank of the entire fund family. The family returns are calculated by using the value weighted return of funds within the same family. D_{large} (D_{small}) is a dummy variable which equals to 1(0) when family *i* is a large (small) fund family. D_{Star} (D_{Dog}) equals to 1(0) when family *i* is a star (dog) family. $\sigma_{\varepsilon}^{2}i,t-1$ is the idiosyncratic risk of family *i* in the ranking period. Funds' daily returns from 3 UK IMA segments, i.e. UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. Panel A reports the results when fund families are sorted by the funds' aggregate market size, while in Panel B results are sorted by the number of funds in the family. Column 1 presents the results when 6 months is considered as the ranking period and column 2 shows the results when the ranking period is 7 months and the post-ranking period is 5 months. Columns 4-6 report the results when a quarterly tournament is considered. The model is estimated by the fixed effect panel regression in which year and entity effects are controlled by adding both year and fund entity dummies to the model. ***, ** and * indicate significance at the 1%, 5% and 10% level.

3.5.3 Rank transition analysis

We now move to examine performance consequences of both the segment and family tournaments. As a first step, in this section we analyse funds' rank transitions. Table 3.10 reports the transition probability of funds' segment ranks. In the first column, we sort all the funds into 10 deciles in ascending order according to their segment ranks. As such, the 1st decile includes bottom ranked funds while the 10th decile contains top ranked funds. The remaining columns present the probability of funds ranked in each of the deciles moving to the other deciles.

We find that the performance of top ranked funds persists for the ranking period and the post-ranking period. The transition probability of staying in the 10th decile is the highest, with a probability of 28.69% of the funds remaining in the same decile in the second half of the year. The transition probability of remaining in the 1st decile is the second highest value. Thus, the very best and worst-performing funds seem to show performance persistency throughout the sample period. It is also the case that the probability for top ranked funds to have extremely bad performance in the second half of the year increases, particularly when their ranks are higher in the first half of the year. That is, funds located in the 10th, 9th, 8th and 7th deciles have a cumulative probability of being demoted to a decile lower than or equal to the 3rd decile of 21.54%, 26.34%, 23%, and 27.73%, respectively. Top performing managers, therefore, are capable of retaining their positions. On the other hand, bottom ranked funds seem to have more difficulty in being promoted to higher ranking groups.

Table 3.10 Segment rank transition matrix

Panel A Current Decile	1	2	3	4	5	6	7	8	9	10
1	0.1930	0.1004	0.1471	0.0786	0.1085	0.0639	0.1239	0.0643	0.0497	0.0710
2	0.1012	0.1513	0.1059	0.1329	0.0911	0.0856	0.0826	0.1078	0.0744	0.0678
3	0.1342	0.1083	0.0764	0.1333	0.1152	0.1394	0.0982	0.0721	0.0712	0.0510
4	0.0807	0.0863	0.1152	0.1275	0.1378	0.1137	0.1051	0.0957	0.0832	0.0547
5	0.0834	0.1365	0.1219	0.1113	0.0727	0.1170	0.1200	0.0927	0.0660	0.0787
6	0.0940	0.1115	0.0940	0.0782	0.1169	0.0971	0.1173	0.1257	0.0838	0.0814
7	0.0673	0.0949	0.1151	0.0799	0.1339	0.0847	0.1099	0.1108	0.1151	0.0887
8	0.0990	0.0528	0.0782	0.0961	0.0965	0.0864	0.0814	0.1158	0.1623	0.1313
9	0.0999	0.0984	0.0651	0.0733	0.0948	0.1187	0.0736	0.1034	0.1370	0.1362
10	0.1021	0.0566	0.0567	0.0746	0.0486	0.0670	0.0635	0.1027	0.1417	0.2869
Panel B Current Decile	1	2	3	4	5	6	7	8	9	10
1	0.1806	0.1055	0.1415	0.0992	0.0831	0.1071	0.0874	0.0601	0.0646	0.0711
2	0.1002	0.1512	0.0740	0.0941	0.1477	0.0991	0.0879	0.105	0.0859	0.0548
3	0.1071	0.115	0.1571	0.0796	0.1138	0.0809	0.1096	0.0852	0.0686	0.0829
4	0.0814	0.0952	0.0908	0.1684	0.0837	0.1543	0.1137	0.0729	0.0778	0.0618
5	0.1030	0.1152	0.1339	0.1323	0.1083	0.0854	0.0786	0.1055	0.0845	0.0531
6	0.1110	0.1262	0.1018	0.0745	0.1171	0.0724	0.1057	0.1047	0.1023	0.0844
7	0.0753	0.0641	0.0718	0.1073	0.1259	0.0959	0.1231	0.1177	0.1216	0.0971
8	0.1216	0.0970	0.0610	0.1109	0.0755	0.1111	0.0843	0.1204	0.0986	0.1196
9	0.0843	0.0667	0.0592	0.0633	0.0814	0.1021	0.1115	0.1072	0.1261	0.1989
10	0.0927	0.0617	0.0822	0.0544	0.0782	0.0638	0.0744	0.1112	0.1528	0.2289

Notes: This table reports the transition probability of the return ranks between the ranking and post-ranking periods. Funds are ranked in ascending order into 10 deciles compared with the mean returns from other funds in the same segment during the ranking period. Columns 2 to 11 report the transition probability of rank shifting for funds in each decile from the ranking period to the post-ranking period. Panel A reports the transition probability on a mid-year basis while Panel B considers a 7-month ranking period. All the figures reported here are in percentage value.

We then switch our attention to the transition probability of the family ranks. A transition matrix similar to that in Table 3.10 is developed in Table 3.11. However, instead of using the segment ranks, in the first column of Table 3.11 we group all the sample funds into 5 percentiles according to their family ranks. For example, the 1st percentile group contains all funds that are ranked in the bottom 20% within their affiliated families, while funds within the 5th percentile group are ranked in the top 20% by their average returns. The results are found to be similar to those in the transition matrix of the segment ranks. Performance of the top and bottom ranked funds persists over time. Funds in the 1st percentile group have a 32.04% probability of staying in the same group and 32.44% of the funds in the 5th percentile group will keep performing at the high level. Panel B of Table 3.11 confirms a similar outcome.

As shown in Tables 3.10 and 3.11, we use the transition probability to provide a general picture of funds' performance persistence over the sample interval. Evidence shows that both the leading funds and the losing funds have higher probability to retain their positions. However, the analytics in Tables 3.10 and 3.11 take no consideration of managers' possible risk shifting. HSZ argue that if risk taking brings no improvement to funds' performance, the motivation left could be driven by either inferior ability or the agency problem. But, compared with the segment tournament, funds in family tournament can win the opportunity to gain benefits from family favouritism. Therefore, the motivation behind risk taking in family tournament is in line with investors' interests. This prompts us to further examine how funds' performance responds to managers' risk taking in family tournaments.

Table 3.11 Family rank transition matrix

Panel A Current Percentile	1	2	3	4	5
1	0.3204	0.2262	0.1792	0.1521	0.1223
2	0.2117	0.2622	0.2615	0.1371	0.1277
3	0.2078	0.1499	0.1793	0.1813	0.2820
4	0.1602	0.2189	0.2349	0.2257	0.1602
5	0.1327	0.1272	0.1271	0.2891	0.3244
Panel B Current Percentile	1	2	3	4	5
1	0.3319	0.2284	0.1277	0.136	0.1763
2	0.2055	0.2352	0.2733	0.1778	0.1082
3	0.1854	0.1873	0.2282	0.2342	0.1653
4	0.1993	0.1889	0.1584	0.2184	0.2352
5	0.115	0.1431	0.1947	0.222	0.3255

Notes: This table reports the probability of return rank transition between the ranking and post-ranking periods. Fund families are ranked in ascending order into 5 deciles according to their value weighted family returns during the ranking period. Columns 2 to 6 report the transition probability of rank shifting in each decile from the ranking period to the post-ranking period. Panel A reports the transition probability on a middle year basis while in Panel B a 7 month period is considered for the ranking period. All values reported in the table are in percentage.

Table 3.12 presents examination results of the transition probability of family ranks under various levels of risk shifting. In the first column we create 5 groups by ranking funds in ascending order according to their levels of risk shifting between the ranking and post-ranking periods. In the second column we further sort all funds by their performance into 3 percentile groups; i.e., funds in the 1st group have performance ranked within the bottom 33% percentile, and so on. For each risk shifting group Table 3.12 reports the transition probability of moving from one percentile to another. We use both the mean returns and the 4-factor model alphas to evaluate funds' performance. It comes as no surprise that, once again, relative performance of the top and bottom ranked funds in the same family persists over time.

Moreover, Table 3.12 suggests that the transition probability of top ranked funds reduces with the increase in risk altering. Of the sample funds, 58.5% of the top funds stay in the same percentile group when the magnitude of changes in the risk taking level is low. This percentage value decreases to 50% when risk changes are more substantial. However, the opposite result is found when performance is estimated with the 4-factor model alpha. In the last column of Table 3.12 the transition probability in the 1st RS group increases from 48% to 58.7%, an increase of 10%. This gives some supportive evidence that risk shifting can lead to the promotion/demotion of family ranks.

Taking Jensen alphas as indication of managers' stock selection ability, the raw returns contain information about the performance that certain funds may deliver. Unlike the risk taking in segment tournaments, in family tournaments none of the performance measures show any improvement after altering the risk exposure. We believe that risk shifting could be an indication of managers' superior ability. Since top managers may already be rewarded by the fund company after mid-year ranking, funds may therefore profitably utilise the information advantage to purchase more under-priced stocks or increase portfolio concentration.

Equities that may have helped funds gain a top ranking are normally funds' major holdings, although they could experience mean reversion in their returns during the second half of the year. It is then expensive for the funds to ditch these holdings, and this is especially so for large funds, as they are more likely to engage in family tournaments. In addition, the agency problem could be another reason for funds to close those long positions. On the other hand, no clear trend is detected in our empirical investigation of bottom ranked funds improving their ranking by increasing the risk taking, consistent with our earlier analysis showing that mid-year losers are not actively involved in family tournaments.

Table 3.12 Risk shifting and post-ranking performance transition

RS ranking	Current percentile	Raw returns			4-factor alphas		
		1	2	3	1	2	3
1	1	0.4824	0.3978	0.1193	0.5779	0.3201	0.1021
	2	0.2443	0.6279	0.1281	0.2668	0.6340	0.0999
	3	0.1375	0.2763	0.5849	0.1634	0.3576	0.4800
2	1	0.4021	0.4543	0.1444	0.4582	0.3754	0.1671
	2	0.1855	0.6687	0.1442	0.1500	0.6957	0.1543
	3	0.1500	0.3421	0.5079	0.1825	0.3459	0.4712
3	1	0.4642	0.4113	0.1253	0.4453	0.4374	0.1182
	2	0.1411	0.7214	0.1379	0.1258	0.7174	0.1561
	3	0.1787	0.2737	0.5474	0.1467	0.2947	0.5579
4	1	0.3821	0.4406	0.1762	0.3813	0.4432	0.1752
	2	0.1342	0.6945	0.1713	0.1314	0.7121	0.1565
	3	0.1834	0.3755	0.4400	0.1287	0.4048	0.4656
5	1	0.4600	0.4442	0.0969	0.5086	0.3624	0.1292
	2	0.1921	0.6637	0.1464	0.1553	0.6816	0.1628
	3	0.1733	0.3268	0.5000	0.1382	0.2748	0.5873

Notes: This table shows mean performance of the funds subsequent to risk shifting. In Column 1, all sample funds are ranked in ascending order in terms of the magnitude of risk shifting, leading to the formation of 5 groups. In Column 2, funds in each of the risk shifting groups are further ranked into 3 groups in ascending order based on their mean returns in the first half of the year. The subsequent family performance is then calculated for each of the risk shifting groups and for the corresponding return ranking groups. Columns 3 to 8 report the transition probability of each percentile's rank shifting between the ranking period and the post-ranking period. The post-ranking performance is measured by funds' mean returns and funds' alphas estimated from the Carhart 4 factors model.

3.5.4 Performance comparison in family tournaments

Despite the evidence of top funds' performance persistence after risk shifting, it remains to be seen whether such funds can outperform their peers in the same family. To answer this question, in this section we compare the performance between the mid-year winners and losers under different levels of risk shifting. The results are reported in Tables 3.13 to 3.15.

In the first column of Table 3.13, we sort funds into 5 groups (RS group) according to their levels of risk shifting. The funds are then classified into the winner and loser groups according to their mid-year performance. Performance of the funds is measured by the mean returns, the CAPM alphas, the 3-factor alphas and the 4-factor alphas. In Panel A where the funds' segment ranks are used to sort winner/loser groups, we find that the losing funds cannot outperform the winning ones for all evaluation measures when their risk taking is at a low level. The mean returns from the winning group exceed those of the losing group by 3.74%, statistically significant at the 1% level. Similar results can be drawn when the Jensen alpha measure is used. However, the winning funds cannot beat the losing ones when they take more risk, since the performance differences between the two groups are not statistically significant for the 5th RS group. Recalling the results in Table 2, where the mid-year losers tend to increase their risk exposure more than the winners in segment tournaments, the performance consequences of funds' risk shifting, however, suggest that it does not make sense for the losing funds to take extra risks. Therefore, winner's risk increasing cannot but be an indication of inferior ability or a sign of the agency problem (see similar argument in HSZ).

In Panel B of Table 3.13, family ranks are used to sort funds into winning and losing groups. We find similar results, that mid-year winners outperform the losers in the 1st RS group. However, at a higher level of risk shifting, Table 3.13 shows a mixed result between performance measures based on raw returns and Jensen alphas. Specifically, mid-year losers can beat the winners in terms of observed returns, but underperform them in Jensen alpha. The difference is -5.34% in returns and 3.59% in CAPM alpha; both are significant at the 1% level. Such differences become smaller when the 3-factor and 4-factor alphas are considered, but remain statistically significant. Certainly, winners' underperformance could be due to mean revision in their main holdings' returns. In Table 3.6, our results have already shown that increasing portfolios' market beta can be a channel of risk shifting. Fund managers may deliberately select large-cap equities with good past performance, or keep the position of their original holdings to maintain their leading positions. But those equities might not perform persistently, which can lower the overall returns of the winners.

On the other hand, the higher value of Jensen alphas delivered by the mid-year winners implies that those managers possess superior stock selection abilities so that they are able to re-construct their portfolios by picking up more under-priced stocks. Meanwhile, judging by the increasing magnitude of alphas obtained from the 3-factor model and the 4-factor model, it is plausible that managers' superior ability is not attributable to increased holdings of the size and book to market portfolio, or the momentum portfolio.

In addition, Panel B shows that the mid-year losers tend to keep their risk at a stable level to mimic the performance of the winners, which may explain why the performance differences between the winner and loser groups are the smallest. HSZ find the similar result that funds with more stable risk levels exhibit the best performance. In a strategic tournament, mid-year winners show risk taking behaviour similar to that of the mid-year losers, since the winning funds now have more access to new capital to manipulate their portfolios. The performance improvement in terms of the Jensen alphas following changes in the risk taking indicates the superior stock selection ability of the winning managers. But when the magnitude of the risk shifting decreases, the winners lose their competitive edge; hence both winners and losers reduce to adopt a similar investment strategy, and so no performance consequence is shown here. However, in the 1st RS group, where the risk shifting is limited in magnitude or even changes to take on less rather than more risk exposure, mid-year losers still cannot outperform the winners, for the reason that the winners can liquidate some of their holdings to lock on the cash profits (see for example HSZ).

Table 3.14 reports the results when the 7-5 interval is used for the tournament analysis. The results are similar to those of Table 3.13. In Panel A, the winning funds manage to outperform the losing ones in a segment tournament when changes in the level of risk exposure are extremely low. In Panel B, when funds' performance is measured by the raw returns or estimates of the CAPM alphas, we find the same supportive results of performance improvements for the winner funds when extra risks are taken. But the performance differences become statistically insignificant when using the Jensen alphas estimated from the 3-factor and 4-factor models. It follows that the winning funds may engage in portfolio reconstruction only immediately after the mid-year ranking is made as a response to the family tournament. In other words, the risk taking behaviour in a family tournament is more likely to take place on a mid-year basis.

Table 3.15 further extends the investigation to examine the risk taking behaviour at the level of a fund family. We create one portfolio for each of the families by using value weighted returns of the funds within the same family. Then we estimate the portfolios' alphas and the mean returns as measures of the families' overall performance. Unlike the results found for individual funds, no significant improvement in the family performance can be identified. In the previous analysis of the whole family tournament, we find that families' total risk taking is not closely related to their overall performance ranks. Results in Table 3.15 further confirm that the risk taking by a certain member of a family is not necessarily beneficial to the performance of the whole family, since the fund company might re-allocate resources from the losing fund to the leading funds that it favours.

Our performance consequences analysis documents a mixed relation between the performance differences and risk taking. Mid-year winners outperform the losing ones by keeping their risk exposure in a low level. But the performance gap in fund alphas decreases and even reversed in observed returns if they take more risk in the second half of the year.

Table 3.13 Post fund ranking performance (6-6)

Panel A	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0355	-0.0019	0.0374***	-0.0003	-0.0271	0.0267**	0.0183	-0.0002	0.0185***	0.0279	0.0025	0.0254***
			(0.0097)			(2.091)			(2.7140)			(3.4388)
2	0.0231	0.0364	-0.0132	0.0005	0.0104	-0.0099	0.0383	0.0370	0.0013	0.0452	0.0419	0.0033
			(-0.9775)			(-1.0527)			(0.2403)			(0.5689)
3	0.0166	0.0351	-0.0185*	0.0001	0.0101	-0.0010*	0.0424	0.0405	0.0018	0.0486	0.0480	0.0006
			(-1.4556)			(-1.2248)			(0.3282)			(0.1027)
4	0.0370	0.0166	0.0203**	0.0080	0.0006	0.0074	0.0465	0.0459	0.0005	0.0526	0.0526	0.0000
			(1.6038)			(0.4418)			(0.0924)			(0.0005)
5	0.0230	0.0153	0.0076	0.0067	0.0006	0.0062	0.0478	0.0476	0.0002	0.0554	0.0547	0.0008
			(0.5262)			(0.6118)			(0.0363)			(0.1092)

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Table 3.13 Post fund ranking performance (6-6) (Continued)

Panel B	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0601	-0.0108	0.0710***	0.0176	-0.0337	0.0513***	0.0202	0.0031	0.0171***	0.0305	0.0069	0.0236***
			(4.5187)			(4.0839)			(0.0062)			(3.1898)
2	0.0378	0.0217	0.0161	0.0083	0.0024	0.0060	0.0366	0.0387	-0.0021	0.0424	0.0447	-0.0023
			(1.1902)			(0.6350)			(-0.3899)			(-0.4055)
3	0.0243	0.0277	-0.0034	0.0040	0.0065	-0.0025	0.0424	0.0406	0.0019	0.0486	0.0480	0.0006
			(-0.2638)			(-0.3043)			(0.3348)			(0.1034)
4	0.0278	0.0236	0.0042	0.0076	0.0088	-0.0012	0.0410	0.0508	-0.0098**	0.0457	0.0588	-0.0132**
			(0.3287)			(-0.1716)			(-1.7245)			(-2.1958)
5	-0.0120	0.0414	-0.0534***	0.0186	-0.0173	0.0359***	0.0527	0.0440	0.0086**	0.0601	0.0513	0.0088**
			(-3.6902)			(3.5781)			(1.7025)			(1.6651)

Notes: This table presents funds' mean performance subsequent to risk shifting on a half year basis. In Column 1, funds are ranked in ascending order to form 5 groups based on the magnitude of risk shifting. Funds are further sorted into the winner (loser) group if their half year performance is higher (lower) than the median performance. Panel A reports the results when a segment rank is considered, while family rank is considered in Panel B. The subsequent fund performance is calculated for each of the risk shifting groups and the corresponding winner and loser groups. The differences between the winner and loser groups are presented for each type of performance evaluation, with t statistics in brackets. All results reported are in percentage values. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.14 Post fund ranking performance (7-5)

Panel A	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0384	-0.0101	0.0485***	0.0056	-0.0334	0.0390***	0.0202	0.0024	0.0178***	0.0258	0.0071	0.0187***
			(3.1484)			(3.0688)			(2.6831)			(2.5370)
2	0.0343	0.0298	0.0045	0.0074	0.0072	0.0002	0.0420	0.0389	0.0031	0.0460	0.0454	0.0006
			(0.3498)			(0.0187)			(0.5206)			(0.0897)
3	0.0251	0.0347	-0.0096	0.0014	0.0123	-0.0109*	0.0460	0.0411	0.0049	0.0524	0.0459	0.0065
			(-0.8053)			(-1.2877)			(0.8053)			(1.0068)
4	0.0316	0.0307	0.0008	0.0138	0.0110	0.0028	0.0519	0.0525	-0.0006	0.0587	0.0577	0.0010
			(0.0690)			(0.3625)			(-0.1036)			(0.1546)
5	0.0240	0.0251	-0.0011	0.0106	0.0080	0.0026	0.0574	0.0493	0.0081*	0.0659	0.0556	0.0103*
			(-0.0782)			(0.2466)			(1.2154)			(1.4723)

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Table 3.14 Post fund ranking performance (7-5) (Continued)

Panel B	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0642	-0.0208	0.0850***	0.0257	-0.0414	0.0672***	0.0233	0.0039	0.0193***	0.0297	0.0082	0.0215***
			(5.7264)			(5.4797)			(2.9594)			(2.9591)
2	0.0401	0.0256	0.0145*	0.0111	0.0044	0.0067	0.0399	0.0408	-0.0008	0.0437	0.0473	-0.0036
			(1.1271)			(0.7252)			(-0.1414)			(-0.5535)
3	0.0292	0.0311	-0.0019	0.0035	0.0103	-0.0068	0.0422	0.0444	-0.0022	0.0481	0.0497	-0.0016
			(-0.1574)			(-0.8003)			(-0.3573)			(-0.2448)
4	0.0025	0.0371	-0.0121	0.0060	0.0184	-0.0124**	0.0506	0.0538	-0.0032	0.0551	0.0611	-0.0059
			(-1.0123)			(-1.6070)			(-0.5457)			(-0.9408)
5	-0.0075	0.0489	-0.0563***	0.0260	-0.0013	0.0390***	0.0558	0.0510	0.0047	0.0635	0.0581	0.0055
			(-4.0016)			(3.7230)			(0.7045)			(0.7700)

Notes: This table presents the funds' mean performance subsequent to risk shifting on a 7-5 month basis. In Column 1, funds are ranked in ascending order to form 5 groups on the basis of the magnitude of risk shifting. Funds are further sorted into the winner (loser) group if their 7-month mean performance is higher (lower) than the median performance. Panel A reports the results when a segment rank is considered, while family rank is considered in Panel B. The subsequent fund performance is calculated for each of the risk shifting groups and the corresponding winner and loser groups. The differences between the winner and loser groups are presented for each type of performance evaluation, with t statistics in brackets. All results reported are in percentage values. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 3.15 Post family ranking performance

Panel A	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0239	0.0023	0.0013	-0.0013	0.0021	-0.0034	0.0247	0.0295	-0.0048	0.0237	0.0291	-0.0054
			(0.0427)			(-0.1614)			(-0.4350)			(-0.4883)
2	0.0272	0.0232	0.0040	0.0002	0.0040	-0.0038	0.0341	0.0308	0.0034	0.0345	0.0307	0.0038
			(0.1489)			(-0.2205)			(0.3278)			(0.3697)
3	0.0296	0.0237	0.0059	0.0051	0.0062	-0.0011	0.0357	0.0486	-0.0129*	0.0362	0.0468	-0.0106
			(0.2177)			(-0.0709)			(-1.2868)			(-1.0145)
4	0.0306	0.0151	0.0155	0.0110	-0.0023	0.0133	0.0445	0.0443	0.0002	0.0452	0.0437	0.0015
			(0.5716)			(0.8253)			(0.0164)			(0.1289)
5	0.0154	0.0151	0.0004	-0.0016	-0.0032	0.0016	0.0349	0.0045	-0.0102	0.0356	0.0456	-0.0010
			(0.0113)			(0.0727)			(-0.6655)			(-0.6291)

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Table 3.15 Post family ranking performance (Continued)

Panel B	Raw returns			CAPM alphas			FF alphas			Carhart alphas		
RS	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0430	0.0006	0.0424**	0.0120	-0.0151	0.0271*	0.0255	0.0309	-0.0054	0.0219	0.0319	-0.0100
			(1.5279)			(1.3100)			(-0.5015)			(-0.9193)
2	0.0411	0.0218	0.0193	0.0087	0.0071	0.0017	0.0315	0.0428	-0.0113	0.0309	0.0418	-0.0109
			(0.7714)			(0.0984)			(-0.9372)			(-0.8721)
3	0.0243	0.0390	-0.0147	-0.0007	0.0137	-0.0144	0.0385	0.0449	-0.0064	0.0393	0.0422	-0.0030
			(-0.5824)			(-0.8845)			(-0.6031)			(-0.2709)
4	0.0287	0.0255	0.0032	0.0078	0.0078	0.0000	0.0477	0.0477	0.0000	0.0474	0.0475	-0.0001
			(0.1305)			(-0.0007)			(-0.0041)			(-0.0080)
5	0.0118	0.0387	-0.0269	0.0033	0.0108	-0.0075	0.0526	0.0460	0.0067	0.0539	0.0462	0.0077
			(-0.8611)			(-0.3144)			(0.4180)			(0.4700)

Notes: This table presents the mean performance of fund families subsequent to risk shifting. In Column 1, families are ranked in ascending order to form 5 groups on the basis of the magnitude of risk shifting. Fund families are further sorted into the winner (loser) group if their half-year performance is higher (lower) than the median performance. Panel A reports the results when risk shifting is on a half year basis, while a 7-5 month risk shifting is considered in Panel B. The subsequent family performance is calculated for each of the risk shifting groups and the corresponding winner and loser groups. The differences between the winner and loser groups are presented for each type of performance evaluation, with t statistics in brackets. All results reported are in percentage values. ***, ** and * indicate significance at the 1%, 5% and 10% level.

We find strong negative correlation between performance consequences and the risk shifting in relation to the systematic risk. Table 3.16 reports the results. Rather than the mixed relation found in the previous table, Panels A and B of Table 3.16 indicate that the average fund performance decreases monotonically when taking more systematic risk. For example, the return difference between the winner and loser group is 3.88 basis points in the 1st RS group but decreases to -2.47 basis points in the 5th RS group. The performance difference in terms of the Carhart alphas also decreases from 2 to -0.93 basis points. Similar results can be found in Panel B. We therefore argue that the performance improvement found in the family tournament in the previous analysis cannot be attributed to the increased exposure to systematic risk, since a positive relation is documented in previous analysis, suggesting that winning funds tend to increase their market beta in the second half of the year. As mentioned before, an increase in the systematic risk is an indication of the enlargement of the holdings of stocks that have heavy weight in the market index. Despite the efforts of winning managers to shift portfolio composition to absorb more highly valued equities, mean revision of the returns of these stocks can demote winners' leading positions.

Results in Panels C and D do not show a clear pattern in the relation between performance consequences and the level of change in the idiosyncratic risks. This finding also confirms the previous results, whereby no significant changes in idiosyncratic risk take place in response to funds' family ranks.

Table 3.16 Post-ranking risk characteristics

Panel A	Raw returns			Carhart alphas		
Beta RS	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0531	0.0143	0.0388***	0.0587	0.0386	0.0200***
			(3.1879)			(3.1080)
2	0.0328	0.0221	0.0107	0.0430	0.0433	-0.0003
			(0.6057)			(-0.0326)
3	0.0496	0.0096	0.0400***	0.0514	0.0412	0.0102*
			(2.4643)			(1.4653)
4	0.0177	0.0314	-0.0231	0.0442	0.0409	0.0033
			(-0.8518)			(0.4735)
5	0.0100	0.0348	-0.0247**	0.0373	0.0466	-0.0093*
			(-1.9387)			(-1.6248)

Panel B	Raw returns			Carhart alphas		
Beta RS	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0589	0.0183	0.0407***	0.0499	0.0490	0.0009
			(3.3941)			(0.1275)
2	0.0406	0.0124	0.0281***	0.0498	0.0384	0.0114*
			(1.7062)			(1.4163)
3	0.0265	0.0287	-0.0022	0.0463	0.0413	0.0050
			(-0.1388)			(0.6551)
4	0.0363	0.0249	0.0114	0.0052	0.0510	0.0006
			(0.7625)			(0.0746)
5	0.0112	0.0474	-0.0362***	0.0449	0.0414	0.0035
			(-2.9690)			(0.5826)

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Table 3.16 Post-ranking risk characteristics (Continued)

Panel C	Raw returns			Carhart alphas		
Idio RS	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0210	0.0257	-0.0047	0.0428	0.0394	0.0035
			(-0.3663)			(0.5746)
2	0.0480	0.0130	0.0350**	0.0373	0.0472	-0.0010
			(2.0467)			(-1.1615)
3	0.0250	0.0267	-0.0017	0.0454	0.0412	0.0042
			(-0.1045)			(0.6510)
4	0.0251	0.0169	0.0082	0.0462	0.0363	0.0099*
			(0.5124)			(1.4110)
5	0.0287	0.0149	0.0138	0.0486	0.0437	0.0049
			(1.1038)			(0.7829)

Panel D	Raw returns			Carhart alphas		
Idio RS	Winner	Loser	W-L	Winner	Loser	W-L
1	0.0269	0.0271	-0.0003	0.0398	0.0451	-0.0052
			(-0.0200)			(-0.8219)
2	0.0338	0.0243	0.0094	0.0386	0.0532	-0.0146**
			(0.5925)			(-1.6336)
3	0.0273	0.0278	-0.0005	0.0416	0.0451	-0.0036
			(-0.0341)			(-0.5169)
4	0.0267	0.0269	-0.0002	0.0579	0.0299	0.0280***
			(-0.0122)			(3.8324)
5	0.0347	0.0144	0.0203***	0.0516	0.0451	0.0066
			(1.6979)			(0.9977)

Notes: This table presents the fund performance subsequent to risk shifting in terms of the systematic and the idiosyncratic risks. In Column 1, funds are ranked in ascending order to form 5 groups according to the magnitude of risk shifting. Panels A and B (C and D) report the results based on sorting by systematic risk (idiosyncratic risk) on a 6-6 and 7-5 basis, respectively. Funds are further sorted into the winner (loser) group if their performance is higher (lower) than the median performance of the family. The subsequent fund performance is calculated for each of the risk shifting groups and the corresponding winner and loser groups. The differences between the winner and loser groups are presented for each type of performance evaluation, with t statistics in brackets. All results reported are in percentage values. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Previous literature suggests that fund families may increase cross-sectional volatility of funds returns to increase the probability of creating star funds. Given the spillover effects of fund flows and the disproportionate response of cash inflows to funds' historical performance, fund families have incentives to encourage risk taking in family tournaments. This requires us to further examine the performance consequences with respect to the efforts by the fund family to promote risk taking.

Table 3.17 documents a strong relation between the performance improvement and the increase in cross-sectional risks within the fund family. Specifically, dog families are found to significantly increase their cross-sectional total risks to improve performance ranking of their underlying funds. For example, the coefficients on $\Delta\Lambda_{i,t}^{\sigma} \cdot D_{Dog}$ are 4.174, 2.391, 4.005 and 3.225 when fund performance is estimated by the mean returns, CAPM alphas, FF alphas and Carhart alphas, respectively. All of them are significant and the performance consequences respond positively. These results suggest that families with extremely underperforming funds are strongly motivated to promote risk taking of their underlying funds. Moreover, we also find some evidence to support a close relation between the increase of cross-sectional idiosyncratic risks and the probability of funds in the dog families being promoted, i.e. $\Delta\Lambda_{i,t}^{\varepsilon} \cdot D_{Dog}$ has a coefficient equal to 1.189 when mean returns are considered for ranking, and this increases to 1.264 and 1.260 when FF alphas or Carhart alphas are used. Dog families contain funds that are ranked in the bottom 10% of the segment and none of their members have top performance. Therefore, they are motivated to undertake various strategies to create stars. Despite this, our results in Table 3.17 imply that dog families improve performance of a certain member by sacrificing the profits of others. In addition to funds' total risk, changes in cross-sectional idiosyncratic risk can also be a channel to improve performance. Thus, fund families may increase industrial concentration in the holdings of a certain fund and diversify the holdings of others to bet on the market.

However, we find only weak evidence to suggest such a strategy in the star families. For example, the coefficients on $\Delta\Lambda^{\sigma}_{i,t} \cdot D_{Star}$ are in lower values, equalling to 1.351 when raw returns are used and 1.321 when Carhart alphas are used for measurement of the performance, and only significant at the 10% significance level. It is plausible that the star funds are already rewarded with increased cash inflows, which can also benefit other peer funds for their performance enhancement.

Table 3.17 also documents a significant relation between performance improvement and the shifting funds' idiosyncratic risk, which is consistent with previous results. But it seems to have lesser power in explaining the aggregated rank promotion compared with the contribution made by the changes in cross-sectional risk. Moreover, no conclusive evidence can be found that shifting of the systematic risk exposure is related to the increases in the aggregate performance ranks.

Table 3.17 Aggregate family ranks analysis

Odds ratio	Raw returns	CAPM alphas	FF alphas	Carhart alphas
$R_{i,t}^{\Delta\sigma}$	0.5823**	0.8432**	0.7879**	0.6332*
	(-2.01)	(-2.14)	(-2.33)	(-1.72)
$\Delta\Lambda_{i,t}^{\sigma} \cdot D_{Star}$	1.3513*	1.3000*	1.4057*	1.3210*
	(1.64)	(1.61)	(1.72)	(1.61)
$\Delta\Lambda_{i,t}^{\sigma} \cdot D_{Dog}$	4.1746***	2.3906**	4.0048***	3.2247**
	(3.08)	(2.01)	(2.94)	(2.52)
$\Delta\Lambda_{i,t}^{\sigma} \cdot D_{Star,Dog}$	0.8541	0.9473	0.8273	0.8463
	(-0.91)	(-0.32)	(-1.04)	(-0.92)
$\Delta\Lambda_{i,t}^{\beta} \cdot D_{Star}$	1.0000	0.9999	0.9999	0.9999
	(-0.06)	(-0.54)	(-0.70)	(-0.82)
$\Delta\Lambda_{i,t}^{\beta} \cdot D_{Dog}$	0.9999	0.9999	1.0000	0.9999
	(-1.18)	(-0.72)	(-0.40)	(-0.53)
$\Delta\Lambda_{i,t}^{\beta} \cdot D_{Star,Dog}$	1.0000	1.0013	1.0000	1.0000
	(0.87)	(0.67)	(0.17)	(0.43)
$\Delta\Lambda_{i,t}^{\varepsilon} \cdot D_{Star}$	1.0026	0.9847	0.9979	1.0213
	(0.04)	(-0.21)	(-0.02)	(0.28)
$\Delta\Lambda_{i,t}^{\varepsilon} \cdot D_{Dog}$	1.1889*	1.1846*	1.2642***	1.2100**
	(1.89)	(1.86)	(2.64)	(2.20)
$\Delta\Lambda_{i,t}^{\varepsilon} \cdot D_{Star,Dog}$	0.9141	0.9428	0.9844	0.9908
	(-1.21)	(-0.85)	(-0.24)	(-0.13)
R^2	26.90	14.61	25.29	21.22
Obs.	534	534	534	534

Notes: This table presents the odds ratios from the post-ranking performance analysis of model (3.2). Fund families are ranked according to performance changes of the underlying members. Fund performance is estimated by four evaluation measures: the raw total returns, the CAPM alphas, the Fama French alphas and the Carhart alphas. $\Delta\Lambda_{i,t}^{\sigma}$, $\Delta\Lambda_{i,t}^{\beta}$ and $\Delta\sigma_{i,t}^{\varepsilon}$ are the cross sectional risk difference on funds' total risk, the systematic risk and the idiosyncratic risk between the ranking and post-ranking period, respectively. $R_{i,t}^{\Delta\sigma}$ is the family rank that measures the level of risk shifting for individual funds within the family. D_{Star} (D_{Dog}) is equal to 1(0) when the family is a star (dog) family. $D_{Star,Dog}$ is equal to 1 if the family has both star and dog funds and 0 otherwise. The model is fitted by the ordinal logistic model. The z statistics are shown in brackets. ***, ** and * indicate significance at the 1%, 5% and 10%.

3.5.5 Cross-fund subsidisation in family tournament

In this section, we examine the fund family's strategy of cross-fund subsidisation. The above research documents that mid-year winners outperform the losers in the risk-adjusted returns by increasing their risk exposure, but the situation reverses when it turns to observed returns. We argue that it might be due to managers' intention to signal the fund family about their superior skills in order to gain additional resource from the fund family. Gaspar et al. (2006) suggests an empirical method to test the strategy of family's cross-fund subsidisation which can be considered as the major channel for the family to promote their favourite funds. To address our concerns regarding to the family favouritism as the reward of higher risk-adjusted returns, we modify their method to rank funds according to their Carhart alphas for each month. Funds ranked above the 25th and 75th percentile are formed as the Low and High value group, respectively. We then construct two sets of High/Low value pairs. In the actual pair, each of the funds in the High value group is matched with a fund within the same family but in the Low value group. In the second set of the High/Low value pairs, the matching pairs, each of the low value funds in the actual pairs is replaced by a random selected fund within the same ranking percentile as the original low value fund but from a different fund family. The return differences between the High and Low value funds for each pair then act as the dependant variable. The empirical model can be shown as following:

$$R_{i,t}^{H} - R_{i,t}^{L} = \alpha_i + \beta_i^{(1)} D_{i,t}^{Family} + \beta_i^{(2)} D_{i,t}^{Style} + \varepsilon_{i,t} \tag{3.5}$$

where D^{Family} and D^{Style} are the dummy variables that takes the value of 1 when funds within the pair belong to the same family or the same investment style, respectively. If the family does subsidise the managers with superior skill, we expect that the same-family dummy is positively related with the return differences.

The results from model (3.5) are reported in Table 3.18. It is suggested that fund family conduct significant cross-fund subsidisation by shifting performance from high alpha funds to low alpha funds after the mid-year. For example, in Panel A the coefficient of the family dummy suggests that the return difference between the High/Low value funds of the same family is on average 0.82% higher than funds in matching pairs. However, we find opposite results when turning to the first half of the year in Panel A. In Panel C we further examine the cross-fund subsidisation on a monthly basis. We find that the family subsidisation is more pronounced in the second half of the year when most of the coefficients of the same-family dummy is positive and significant from 0.

The above findings support our view regarding the motivation of managers' risk taking in the family tournament. Specifically, funds with high risk-adjusted returns gain benefits through the cross-fund subsidisation which can drive managers' intention of active trading. The results also indicate that the fund family consider managers' skill as the major criteria in judging which fund to be promoted.

Table 3.18 Cross-fund subsidisation

Panel A (1st half year)	Intercept	D^{Family}	D^{Style}
Coeff.	0.1027***	-0.0325***	0.0438***
t-Stat.	(22.62)	(-6.01)	(7.85)
Adjusted R^2	0.16		
Panel B (2nd half year)	Intercept	D^{Family}	D^{Style}
Coeff.	0.0082***	0.0082**	-0.0090**
t-Stat.	(2.20)	(1.99)	(-2.00)
Adjusted R^2	0.09		
Panel C (Monthly)	Intercept	D^{Family}	D^{Style}
Feb.	0.1137***	-0.0170*	0.0515***
	(14.85)	(-1.87)	(5.58)
Mar.	0.1721***	-0.1437***	0.0279*
	(15.67)	(-10.57)	(1.93)
Apr.	0.0405***	-0.0184	0.0520***
	(3.41)	(-1.29)	(3.52)
May	0.0621***	0.0341***	0.0450***
	(9.94)	(4.69)	(6.05)
Jun.	0.0068	0.0557***	-0.0270***
	(0.97)	(6.84)	(-3.27)
Jul.	-0.1491***	0.1536***	-0.0462***
	(-16.30)	(13.78)	(-4.04)
Aug.	-0.0749***	-0.0161	0.0215**
	(-9.94)	(-1.74)	(2.26)
Sep.	0.2225***	-0.2045***	0.0224*
	(19.29)	(-15.23)	(1.64)
Oct.	-0.0140*	0.0315***	0.0230**
	(-1.78)	(3.29)	(2.31)
Nov.	-0.0184**	0.0268***	-0.0359***
	(-2.52)	(3.29)	(-4.40)
Dec.	0.0137*	0.0368***	0.0107
	(1.64)	(3.61)	(0.98)

Notes: This table presents the regression results from the test of cross-fund subsidisation. For each month, we rank all the funds in ascending orders according to their Carhart alphas, and funds within the 25th percentile (75th percentile) are formed to be the Low (High) value fund groups. The comparison peer group is all the funds in the same style. We then construct two sets of High/Low value pairs, namely, the actual pair and the matching pair. In the actual pair, each of the funds in the High value group is matched with a fund of the same family but in the Low value group. In the matching pair, each of the Low value funds in the actual pair is substituted with a fund taken from the same ranking percentile but within a different fund family. The return difference is then computed in the month following the ranking month. D^{Family} is the dummy variable which equals to 1 when the paired funds are in the same fund family. D^{Style} is the same style dummy that takes a value of 1 when the paired funds are within the same investment style. Panel A reports the results when we only consider the subsidisation in the first half of the year while Panel B reports the results from the second half of the year. In Panel C we report the results from the monthly regression. Funds' daily returns from 3 UK IMA segments, UK All Companies, UK Equity Income and UK Small Companies, are examined for the sample years between 2001 and 2010. ***, ** and * indicate significance at the 1%, 5% and 10% level.

3.6 Conclusions

In this research, we analyse the risk taking behaviour in fund family tournaments, and the performance consequences. Using the data from UK unit trusts, our research documents a significant risk taking behaviour in the family tournaments. The half-year winning funds in the family are likely to take more risks than their peers in the same family. On the other hand, winning managers would consider adopting similar risk taking strategies as the losers, since they have competitive advantages over the losers, such as more capital injection and family favouritism. We further examine the relation between the half-year performance and changes in funds' taking of other types of risk. The results show that the winning funds tend to increase their systematic risk in the second half of the year. We argue that this is because those winners want to retain their positions by maintaining or increasing their holdings of high value and index linked equities to mimic the market.

We also analyse that how risk shifting is related to different incentive. By classifying the sampled years into bear and bull market condition, we find a positive relation better risk taking and previous performance in the bear market when mid-year losers are more concerned about their jobs rather than compensation. And such a correlation is more pronounced than the situation in bull market when compensation incentive is dominant.

We then conduct further analysis on the performance consequences of risk shifting.

Results show a strong relation between risk taking and performance changes. Our results regarding to the observed returns are consistent with the previous research in which increasing risk is accompanied with performance drop. But when turning to the risk-adjusted performance, risk shifting is positively correlated to funds' performance. Given that the half-year winners will increase their taking of systematic risk, the deterioration in funds' observed returns seems due to the mean revision of high value equities in portfolio holdings. When risk-adjusted performance is considered, the winning funds outperform the losing ones in the post-ranking period. We argue this is due to managers' intention to show off their skills in order to gain further subsidisation from the fund family. Our empirical results from the test of families' cross-fund subsidisation support this view. In addition, no evidence is found that the increasing of the systematic risk or the idiosyncratic risk can lead to a strong performance improvement.

Our analysis shows that the families that have extremely poor performing funds in their groups would manage to promote segment ranks of most of their underlying funds by increasing the cross-sectional volatility in both total and idiosyncratic risks. This implies that the fund family may sacrifice the profits of certain members to benefit the others, given the disproportionate responses in cash inflows and the spillover effect. Our research thus provides empirical evidence on effects of family tournaments and performance shifting.

CHAPTER FOUR

INVESTORS LEARNING AND MUTUAL FUND FAMILY

4.1 Introduction

Information from the fund family can provide additional insight when evaluating the performance of its underlying funds. It is often the case that funds affiliated to the same fund family share the same investment adviser. Fund family and the fund manager combined contribute to returns gained by a certain fund. The family can influence the performance of the individual funds not only from the administration perspective, but also in terms of the quality of analysis and information flows (Baks, 2003). Meanwhile, the fund family conducts various investment strategies to affect the performance of its underlying funds, for example by increasing the cross-sectional variability to create star funds (Nanda, Wang and Zheng, 2004); engaging in family tournament by encouraging funds to significantly shift their risk exposure (Kempf and Ruenzi, 2008); or transferring performance within the family by cross-fund subsidisation (Gaspar, Massa and Matos, 2006). However, standard performance evaluation literature usually examines the fund performance independently, neglecting the return information provided by the other parties. This research aims to conduct the performance evaluation procedure giving consideration to information provided by other funds as well as the fund family.

The Bayesian framework provides the opportunity to include information other than funds' historical data in the performance evaluation. Pastor and Stambaugh (2002) (PS hereafter) consider a seemingly unrelated model with the Bayesian estimation to include the correlation between the pricing factors and the other non-benchmark portfolios. Busse and Irvine (2006) further apply such a method in the persistence analysis to offer more accurate prediction of funds' alphas. Jones and Shanken (2005) (JS hereafter) are the first to include return information from other funds in estimating funds' alphas, by implementing a dependent prior belief in the Bayesian updating which is defined as cross-fund learning. They argue that in addition to the observed returns, significant randomness of managers' skill also resides in the performance of a certain fund. Therefore, funds' alphas can be measured as the combination of both historical returns and a general view on the skill of the entire group of managers in the fund industry. However, their research does not take into consideration information given by other factors in the pricing model, for example the systematic risk and the idiosyncratic risk taken by other funds.

Bayesian alpha is a pricing model based estimation in which prior information can be included by adding another level to the model. In the seminal work by Lindley and Smith (1972), a general solution to the two level linear model is derived in a Bayesian system, while Smith (1973) extends it to solve a general multilevel linear model. The major problem encountered lies in adding proper prior information on the covariance matrix of all the factors in the model. In CAPM, only a general prior distribution, i.e. an inverse Wishart prior, is applied to represent all the additional information regarding both the alpha and the market beta. However, given that the degree of freedom is the only variable used to define the distribution, it is therefore far from the situation in reality to use the inverse Wishart as the prior belief in the estimation of Bayesian alphas.

We construct a linear hierarchical model to consider the learning across funds within the fund family during the performance evaluation. In order to overcome the restriction noted above and to include return information from the other pricing factors, we apply a separation strategy suggested by several statistical studies to decompose the covariance matrix into the production of the diagonal matrix with variance of each factor, and the correlation matrix of all the factors in the pricing model (see for example Barnard, McCulloch and Meng, 2000; O'Malley and Zaslavsky, 2008). By deploying the separation strategy we can define the prior information on each of the pricing factors as well as the between-factor correlation.

Our results from the simulation suggest that the separation strategy powered performance evaluation better addresses the learning issue. Firstly, we find that given a less dispersed prior belief on managers' inferior ability, the posterior mean on α of each of the underlying funds converges faster than when using the method suggested by JS. Our findings suggest that returns from peer funds within the same fund family can significantly affect investors' updating on fund alphas. Secondly, our method provides a full Bayesian treatment on each of the pricing factors to grasp the specific prior information on all the factors. Our simulation shows that it can improve the level of shrinkage to offer more precise evaluation results if the prior belief is reasonably accurate. One may argue that the results might be sensitive to the selection of prior belief. However, since the Bayesian estimation provides a compromise between the prior belief and the real data, the posterior estimation also contains information from the reality. Thirdly, after decomposing the individual fund α into the combination of the family mean and the idiosyncratic contribution from the manager, we find that the fund manager contributes positively to the overall fund performance whenever prior belief is applied.

Our research is closely related to the method suggested by JS. However, our method differs from theirs in the following aspects. Firstly, our research has a different scope. JS consider the cross-fund learning from the general fund population while our research set to consider the learning across peer funds within the same fund family. We decompose individual fund's alpha into a mean performance and the contribution from managers' idiosyncratic strategy. Secondly, we provide Bayesian treatment on each of the variable considered in the pricing model in addition to the alpha, i.e. the systematic risk; the factor loadings on the size, book to market and the momentum portfolio in order to better address the learning behaviour. By including information given by all pricing factors we manage to find out that from the investors' perspective how beliefs on other issue from the pricing model affect the updating of individual fund alpha. Thirdly, we place no restriction on the correlation matrix of different pricing factors in the pricing model. That is to say we also include prior information to allow cross-factor learning which is often impossible in the conventional OLS estimated alphas.

The rest of the research is organised as follows: We discuss the related literature in the following section. The learning model is derived in section 4.3. We also show the model given by JS which can be regarded as a special case of our model. Section 4.4 discusses the model simulation results by using the hypothetical data as well as the real fund data. The conclusion and implication of this research is summarised in the final section.

4.2 Related literature

Our research regarding the learning across the fund families is related to four strands of literature: the Bayesian based performance evaluation procedure; cross-sectional learning among financial vehicles; performance prediction and persistence analysis, and the covariance separation method used in solving the multilevel linear model. We discuss each of these issues in the following sections.

4.2.1 Bayesian fund performance evaluation

Alpha, or the risk-adjusted return, is widely recognised as the excess performance of a certain mutual fund relative to the returns of the market benchmark. Conventionally, as described by Jensen (1968), it is calculated by applying the OLS estimation on the intercept of the capital asset pricing model (CAPM) by Sharpe (1964) and Lintner (1965). This performance evaluation has evolved with the development of the asset pricing theory to incorporate additional benchmark portfolios, i.e. the size and book to market effect by Fama and French (1993), the momentum effect by Jegadeesh and Titman (1993) and Carhart (1997), and the multiple benchmarks by Elton, Gruber and Blake (1996). Despite the effort of seeking the valid market benchmark in building a solid pricing model, other researches adopt alternative techniques to understand funds' abnormal performance. For example, studies by Kosowski, Timmermann, Wermers and White (2006) and Cuthbertson, Nitzsche and O'Sullivan (2008) apply a bootstrapping method to distinguish alphas that can be attributed to managers' genuine stock selecting skills from those resulting from sample variation.

Although a large body of literature devotes much effort to designing a proper model to estimate funds' alphas, the method used focuses only on the conventional OLS technique with objective statistical settings. More recently, a growing number of studies have shifted their interest to the additional information provided by non-benchmark pricing factors, investors' opinion and returns from other funds. For instance, Baks, Metrick and Wachter (2001) find that certain prior beliefs on managers' skill might justify the investment decision. Busse and Irvine (2006) find evidence to support short-term persistence in funds' performance in a Bayesian setting.

The approach considered by PS provides a Bayesian view in the performance evaluation procedure. Given the fact that most of the mutual funds in the market have much shorter lifetimes than do equities, estimation based on limited data might be biased. Meanwhile, alphas generated from different pricing models are sensitive to the selection of market benchmarks. The market portfolio(s) ignored in a certain pricing model might be related to the benchmark portfolio(s) included in the current model. Therefore, they calculate the funds' alphas in a Bayesian system with the prior belief on the returns of the benchmark (considered in the current pricing model), and the non-benchmark portfolios (ignored in the current pricing model) precede the mutual fund returns. Since the benchmark (non-benchmark) assets have longer return history, such Bayesian settings not only overcome the limited datasets in the estimation, but improve understanding of how the so-called seemingly unrelated assets affect the performance evaluation of a certain fund.

4.2.2 Learning across funds

The dependent nature of the variability of funds' alphas can be modelled in a hierarchical setting in which a dependent prior is designated on the cross-sectional mean. JS first consider a multilevel structure in the performance evaluation with a dependent prior. They suggest that the alpha of a fund can be drawn from a common population distribution which is defined to describe the general belief on the cross-sectional performance. A prior can then be assigned to represent the investors' opinion on the mean of the distribution, since its posterior mean is the weighted average of the information from both the prior and the data. They find that the posterior mean shrinks toward the prior mean when the number of funds included increases; that is, investors are more likely to believe that the manager of a certain fund is unskilful if more funds in the industry give them the same impression. Moreover, if the investors tend to have more homogeneous belief on the absence of fund managers' skill, i.e. the variance of the prior decreases, the shrinkage is also enhanced. In their research, JS call this the performance with learning across funds.

The empirical results from JS also show a large difference in funds' performance between the learning prior and no learning. An individual fund's alpha shrinks toward the prior mean substantially when a less spread prior variance is considered under the no learning prior. When a learning prior is considered, the degree of shrinkage is much lower, since the posterior alpha for a given learning prior is a precision weighted average of not only the individual fund's returns, but the overall view of the entire industry. Therefore, given the consideration that a certain alpha is a random draw from a common population, the alpha based on a fund's own return is more likely to be overvalued (undervalued) if the investor has strong (weak) confidence in the skill of that fund's manager. In this case, a learning prior provides a compromise between the fund's own returns and the cross-sectional performance in the entire industry.

However, since their research only considers the dependent nature of the prior belief on alpha, the evaluation model can be regarded as a special case of the hierarchical varying intercept and varying slope model. In reality, investors may also have heterogeneous belief on the pricing power of the certain factor model used in the performance evaluation, or on the risk exposure to a particular market benchmark. These concerns make it necessary to conduct a general case multilevel model.

4.2.3 Covariance separation strategy

The difficulties with modelling the variance and covariance matrix of a hierarchical model can be resolved through separation; that is, the covariance matrix can be decomposed into a product of diagonal matrix of standard deviations and correlation matrix. In a seminal work by Barnard, McCulloch and Meng (2000), the separation strategy is introduced to improve the convergence and to relax the dimensionality constraint. The technique is to separate the covariance matrix into the diagonal matrix with standard deviations of all parameters at the group level and a correlation matrix which describes the co-movement among those parameters. Thus, in a Bayesian system the prior belief can be applied on each of the parameters at the group level as well as the joint prior distribution of the correlation matrix. In their simulation, they consider a prior belief with log-normal distribution on the regression parameters with a beta distribution on the marginal distribution of the correlation coefficients. The simulation results show a significant degree of shrinkage on the posterior mean when the dispersion of the group means' prior decreases, but such shrinkage is mitigated dramatically when the dispersion reaches a ridiculously high level. In other words, the posterior means converge to their OLS estimations when a diffuse prior is considered. However, the prior on the correlation coefficients remains non-informative due to the absence of prior information.

An important feature of the separation technique is its consideration of specific prior beliefs on certain parameters of interest, i.e. the ability to strengthen the informative level on particular parameters and weaken others. Barnard et al. (2000) designate different priors on the intercepts and market betas in the simulation by using CAPM to mimic the distinct response to the return shifting of market portfolio from different companies within the same industrial sector. The separation technique, therefore, enables the model to capture both the common and distinct features. Furthermore, recent studies introduce a modified separation technique which not only maintains the original key feature, but also improves its efficiency (see Gelman and Hill, 2007; O'Malley and Zaslavsky, 2008). A scaled inverse Wishart distribution is denoted as the prior on the covariance matrix through over-parameterisation, the use of which enhances the convergence substantially.

4.2.4 Persistence in fund performance

From the academic point of view, test results on performance persistence have crucial implications for the validity of the efficient market hypothesis. Evidence of significant persistence would reject its semi-strong form. Meanwhile, the persistence test can also be used to examine the prediction power of a particular pricing model. Thus, it is always worth analysing whether funds' superior performance would persist.

Studies of evaluating managerial ability can be divided into two groups, i.e. the measurements based on stock selection ability and those based on market timing ability. Stock selection ability is reflected in the returns of individual stock predicated by the managers, while market timing refers to the predication of a wide range of financial assets in the whole market. In most of the previous literature, little evidence has been found to support the existence of positive abnormal returns over longer horizons. For example, Jensen (1968) and Elton et al. (1996) use the stock selection measurement in their persistence analysis, while Henriksson (1984) utilises the market timing measurement. Nevertheless, some studies have found persistence over a short horizon to be significant; for example, Brown and Goetzmann (1995), Grinblatt, Titman and Wermers (1995), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (1999). In all of the above research, however, negative excess returns have been found over a period less than one year. On the other hand, based on the finding by Jegadeesh and Titman (1993), some researchers suggest that momentum effect makes the major contribution to the superior performance of top funds (see Grinblatt et al., 1995, Carhart, 1997). Carhart (1997) finds that 4.6% of the contributions to short-term persistence come from the momentum stocks trading, while about 1% is from other common factors. The investment expenses explain much of the persistence. The research also concludes that there is no significant evidence that supports the contribution of skilled or informed fund managers. However, the finding is not robust to different model misspecifications. More recently, Bollen and Busse (2005) use a coexistent model that includes both stock picking and market timing methods in the evaluation of fund performance persistence, and also simulates the investors changing strategies in their portfolio, which makes the research more practical. After applying such a method to daily returns of 230 US equity based funds, they find that performance persistence exists over quarters in top performing funds as well as in poor ones. However, different types of returns used in the research exhibit significant discrepancies when the analysis is applied to both raw returns and risk-adjusted returns.

Busse and Irvine (2006) analyse the funds' performance persistence based on the seemingly unrelated estimation (SURE, hereafter) with the Bayesian learning suggested by PS, which incorporates the idea that non-benchmark portfolio and returns with longer history provide additional information on the pricing model (Stambaugh, 1997). As indicated above, Bayesian alphas not only increase the accuracy of the measurement, but exhibit significant explanation power to predict future performance. Adopting the SURE model, they consider skill variance ranging from 10^{-13} to 10^{-3} and mispricing variance from 10^{-11} to 10^{-4} to address the prior belief on managers' skill and the pricing ability of a certain factor model, respectively. Then the averaged spearman correlation is computed to test the performance persistence. Their results indicate that higher predication power of the SURE model is more likely to be associated with the diffuse skill prior. In other words, funds' abnormal performance is found to persist over a short horizon given the condition of heterogeneous belief on managers' ability. Meanwhile, the results from different pricing models with various mispricing variance suggest that CAPM provides more accurate prediction of funds' alphas when sceptical prior belief is taken on the pricing power of the market factors. The Bayesian SURE model applied in this research can be viewed as a general approach of the factor models, assuming non-benchmark assets provide additional information in the performance evaluation. It takes the additional information provided by the non-benchmark assets into consideration and constructs the persistence test using high frequency data to increase accuracy. However, the independent prior associated with the SURE still raises the issue of ignorance about cross-sectional influences, which, as mentioned in the previous section, may affect the evaluation procedure.

4.3 The performance evaluation model

In order to address the cross-sectional learning among funds, we consider fund companies' evaluation procedure though a hierarchical Bayesian inference, which is described in the following sections. Section 4.3.1 explains the derivation of the Bayesian performance evaluation model. In section 4.3.2, we discuss how evaluation models considered in the prior research can be regarded as a special form of our general learning model. Then, in section 4.3.3, we explain the elicitation of the prior belief applied in the simulation studies.

4.3.1 The general learning model

The learning process considered in this section is similar to the settings of JS, but in a more general framework. We adapt the Bayesian treatment for each of the pricing benchmarks in the factor model. In our evaluation model no restriction is applied on the correlation of different pricing factors, thus the co-movements can be viewed as an unknown variable which is decided by the information mixture of the prior belief and the true data, whereas the conventional OLS estimations might suffer substantial imprecision due to multicollinearity between different regressors. Another important feature of the general learning model is that the dependent prior on the pricing factors enables the model to explain the heterogeneous opinion on the pricing power of a particular factor model. Different prior beliefs on the pricing benchmarks can then be included to address the sensitivity issue of how funds' alphas respond to divergent views on the pricing power of benchmark portfolios. Thus the evaluation model of JS can be regarded as a special case of the general learning model. Meanwhile, instead of gaining information from the entirety of cross-sectional funds in the evaluation, we sort funds into different fund families, since funds within the same family often share the same investment adviser, and they are more likely to set a similar market benchmark to compete with. In addition, fund companies often adopt various family strategies, such as reallocating capital or increasing cross-sectional variance, to achieve better performance for their underlying funds or entire fund families. Therefore, we construct the learning model from a family perspective to incorporate additional return information offered by funds within the same fund family.[7]

A hierarchical linear structure is applied to assess the manager's ability when performance is assumed to vary across the funds managed by the same fund company. To facilitate the estimation of the variables in the multilevel structure a Bayesian system is constructed to conduct the distribution of each variable as a weighted average of both prior belief and real data. We assume in our model that the abnormal performance (alpha) can be attributed to the fund family, the manager and the fund's idiosyncratic risk exposure, which are all assumed to be unknown to both the fund company and the investors. Consider a fund family with a single fund: we assume that the fund's observable performance α_j is the combination of θ, the mean performance for fund j, and t_j, the idiosyncratic risk level for fund j. To address the

[7] Our model can be easily adapted to the research context of JS, where a diffuse prior is designated to each of the pricing factors. Meanwhile, the prior belief can be set to represent the opinion on the performance of the entirety of cross-sectional funds

dependence of the prior we further assume that α_j is a random draw from the unknown distribution $N(m, \sigma_\alpha^2)$ and t_j is defined to follow $N(0, \sigma_j^2)$, where σ_j^2 can be viewed as the deviation from the mean performance of fund *j*. We also consider the similar setting for the other pricing factors in the evaluation model. The prior distribution on α_j, $N(m, \sigma_\alpha^2)$, describes the prior belief of the combined mean performance of both fund manager and fund family. The prior distribution on σ_j^2 is then used to represent the between-variability of α_j for all the funds within the same family.

The posterior distribution is generated through Markov Chain Monte Carlo algorithm (MCMC, hereafter). We derive the Gibbs sampler and the Metropolis-Hastings algorithm for each of the unknown variables in the Bayesian hierarchical linear model described above given a fund family with M funds, since the posterior distribution of all the variables can be written in a closed form except that for the within variability in fund family. Gibbs sampler can update each variable directly at a time when its posterior distribution can be derived in a closed form, while a proposed distribution is needed for the Metropolis-Hastings algorithm to act as a reference for drawing. The notation of the variables is as follows: β, individual fund's factor loadings, σ_j^2, the individual fund's performance measurement error, Θ, the family mean performance, and Λ, the between variation within the fund family.

4.3.1.1 Likelihood function

We now consider the evaluation method of funds' abnormal performance delivered by a certain fund family with M funds. A factor model is adopted to evaluate the performance for each of the funds in a fund family. The likelihood function can be stated as follows:

$$R_j = f_j\beta_j + u_j, \qquad (j = 1, \cdots, M) \tag{4.1}$$

where R is a n_j dimensional vector of fund's excess returns and f is a $n_j \times K$ matrix of the excess returns from $K-1$ market benchmark portfolio(s), of which the first column is all 1. β is K dimensional factor loadings. We assume that $u_j \sim N(0, \sigma_j^2)$, in which u_j is assumed to be homoscedastic and independent of each other.

The family level likelihood function can also be shown to have the following form:

$$\beta_j = X_j\Theta + e_j, \quad (j = 1, \ldots, M) \tag{4.2}$$

where $X_j = I_k \otimes x_j$ is a $K \times K$ matrix of family level predictors, x_j. As suggested in the following simulation study, we assume that x_j equals to 1 for all j. Additional factors can also be incorporated as family level predictors, i.e. the non-benchmark assets in the SURE model. $\Theta = (\theta_1', \ldots, \theta_K')'$ is the mean performance, which describes the combined performance attributed to fund manager as well as the fund family. The prior beliefs on Θ and σ_j^2 are given by $\Theta \sim N(Z\tau, \Delta)$ and $\sigma_j^2 \sim Scale\text{-}inv\text{-}\chi^2(v_j, s_j^2)$, respectively.

We further consider a separation strategy to define the prior on funds' between variation, Λ, in which the family level covariance matrix is decomposed into a combination of diagonal scaled matrix and an unscaled matrix that can describe the correlation of factor loadings among different funds within the same fund family, i.e. $\Lambda = \Xi\Phi\Xi$, where Ξ is a diagonal scaled matrix and Φ is the unscaled matrix.[8] Given Eq(4.1), let $R = (R_1', \ldots, R_M')'$, $F = diag(f_1, \ldots, f_M)$, $\beta = (\beta_1', \ldots, \beta_M')'$ and $N = \sum_{j=1}^{M} n_j$; then we can rewrite Eq(4.1) for *M* funds as

$$R = F\beta + U, \quad U \sim N(0, \Sigma) \tag{4.3}$$

where $\Sigma = diag(\Sigma_1, \ldots, \Sigma_M)$ and $\Sigma_j = \sigma_j^2 I_{n_j}$. The family level likelihood function for *M* funds can also been given by letting $\beta = (\beta_1', \ldots, \beta_M')'$, $X = (X_1, \ldots, X_M)'$ and $\Lambda = I_M \otimes \lambda$, where λ is the covariance matrix for all the factor loadings, β_j. The family level likelihood function for *M* funds then can be written as

$$\beta = X\Theta + E, \quad E \sim N(0, \Lambda) \tag{4.4}$$

where β_j is a $K \times 1$ vector of K factor loadings for each of the M funds. Θ represents the mean value which remains the same across *M* funds, while e_j is the manager's selection of the risk level for fund *j*. For *M* funds, E is assumed to follow a normal distribution with the covariance matrix, Λ. The prior on Λ can then be regarded as the magnitude of how factor loadings of an individual fund deviate from

[8] Gelman and Hill (2007) argue that such over parameterisation not only enables the control of the dispersion level for the factor loadings within the same group, since Φ is close to uniform, it also increases the convergence of the chain. See for example Barnard et al. (2000) and O'Malley and Zaslavsky (2008) for further discussion on the separation strategy and the scaled inverse Wishart distribution.

its group mean. Thus, a prior on fund's alpha with a higher variance suggests a higher cross-sectional variability on alpha within the fund family. We also consider that the prior of the mean value, Θ, follows $N(\zeta, \Delta)$, which represents the beliefs on the family's mean.

4.3.1.2 Posterior distribution of β

In this section we derive the posterior distribution of the factor loadings for *M* funds conditional on R, F and X. Assume that Σ, Θ and Λ are all updated, ζ and Δ are the prior belief on β. The posterior belief of β can be derived as

$$
\begin{aligned}
&P(\beta|R,F,\Sigma,X,\Theta,\Lambda) \propto P(R|\beta,F,\Sigma)P(\beta|X,\Lambda,\zeta,\Delta)\\
&\quad = \mathcal{N}_M(R|F\beta,\Sigma)\mathcal{N}_{MK}(\beta|X\zeta,\Lambda + X\Delta X')\\
&\quad \propto exp\left\{-\frac{1}{2}\left[(R-F\beta)'\Sigma^{-1}(R-F\beta) + (\beta - X\zeta)'(\Lambda + X\Delta X')^{-1}(\beta - X\zeta)\right]\right\}\\
&\quad \propto exp\left\{-\frac{1}{2}\left[\beta'(F'\Sigma^{-1}F + (\Lambda + X\Delta X')^{-1})\beta - 2\beta'(F'\Sigma^{-1}R + (\Lambda + X\Delta X')^{-1}X\zeta)\right]\right\}\\
&\quad \propto exp\left[-\frac{1}{2}(\beta - D_1V_1)'D_1^{-1}(\beta - D_1V_1)\right]
\end{aligned}
$$

So the posterior belief on the fund's factor loadings follows a MK dimensional multivariate normal distribution,

$$\beta|R,\Sigma \sim \mathcal{N}_{MK}(D_1V_1, D_1) \qquad (4.5)$$

where

$$D_1 = [F'\Sigma^{-1}F + (\Lambda + X\Delta X')^{-1}]^{-1}$$

and $V_1 = F'\Sigma^{-1}R + (\Lambda + X\Delta X')^{-1}X\zeta$.

The posterior mean, D_1V_1, of β is a weighted average of the true return data and the prior belief on β. We can further extend $(\Lambda + X\Delta X')^{-1}$ as

$$(\Lambda + X\Delta X')^{-1} = \Lambda^{-1} - \Lambda^{-1}X(X'\Delta^{-1}X)^{-1}X'\Lambda^{-1}$$

Thus, when $\Lambda^{-1} \to 0$ and $\Delta^{-1} \to 0$, the posterior mean of β becomes $D_1V_1 = (F'\Sigma^{-1}F)^{-1}(F'\Sigma^{-1}R)$; that is, the posterior mean of β reduces to its OLS estimates given a diffuse prior on both the cross-sectional variability and the variance of the family level mean.

4.3.1.3 Posterior distribution of Σ

Given β, Θ and Λ, we have

$$P(\Sigma|R, F, \beta) \propto P(R|\beta, F, \Sigma)P(\Sigma)$$

By assumption we have a homoscedastic error term for each fund *j*, which we can write as $\Sigma = I_M \otimes \Sigma_j$. The posterior belief can then be shown as

$$\begin{aligned} P(\sigma_j^2|R_{.j}) &\propto \prod_{i=1}^{n_j} P(R_j|f_{i,j}, \beta_{i,j}, \sigma_j^2)P(\sigma_j^2) \\ &\propto \prod_{i=1}^{n_j} N(R_{i,j}|f_{i,j}\beta_{i,j}, \sigma_j^2)Scale\text{-}inv\text{-}\chi^2(\sigma_j^2|v_j, s_j^2) \\ &\propto (\sigma_j^2)^{-(\frac{n+v_j}{2}+1)}exp\left[-\frac{1}{2\sigma_j^2}(nS_j + v_js_j^2)\right] \end{aligned}$$

Therefore, we have the posterior distribution for σ_j^2 as

$$\sigma_j^2|R_{.j}, \beta \sim Scale\text{-}inv\text{-}\chi^2(n + v_j, \frac{nS_j + v_js_j^2}{n + v_j}) \tag{4.6}$$

where $i = 1, \ldots, n_j$, $j = 1, \ldots, M$ and $S_j = \dfrac{\sum_{i=1}^{n_j}(R_{i,j} - f_j\beta_j)^2}{n_j}$.

4.3.1.4 Posterior distribution of Θ

When β and Λ are both updated by the distribution described in the previous two sections, the posterior belief on Θ can then be derived in a similar fashion given the information of prior distribution $\Theta \sim N(\zeta, \Delta)$,

$$
\begin{aligned}
&P(\Theta|R, F, \Sigma, X, \Lambda, \zeta, \Delta) \propto P(R|F, \Sigma, X, \Theta, \Lambda)P(\Theta|\zeta, \Delta) \\
&\quad = \mathcal{N}_{MK}(R|FX\Theta, \Sigma + F\Lambda F')\mathcal{N}_K(\Theta|\zeta, \Delta) \\
&\quad \propto exp\left\{-\frac{1}{2}\left[(R - FX\Theta)'(\Sigma + F\Lambda F')^{-1}(R - FX\Theta) + (\Theta - \zeta)'\Delta^{-1}(\Theta - \zeta)\right]\right\} \\
&\quad \propto exp\left\{-\frac{1}{2}\left[\Theta'(\Delta^{-1} + X'F'(\Sigma + F\Lambda F')^{-1}FX)\Theta - \Theta'(X'F'(\Sigma + F\Lambda F')^{-1}R + \Delta^{-1}\zeta)\right]\right\}
\end{aligned}
$$

Thus Θ can be shown to follow a K dimensional multivariate normal distribution:

$$\Theta|\beta, \Lambda \sim \mathcal{N}_K(D_2V_2, D_2) \tag{4.7}$$

where

$$D_2 = [\Delta^{-1} + X'F'(\Sigma + F\Lambda F')^{-1}FX]^{-1}$$

$$V_2 = X'F'(\Sigma + F\Lambda F')^{-1}R + \Delta^{-1}\zeta$$

The posterior mean of Θ has a similar form as those defined for β in the previous section. However, if $\Delta^{-1} \to 0$, the posterior mean of Θ equals to $[X'F'(\Sigma + F\Lambda F')^{-1}FX]^{-1}[X'F'(\Sigma + F\Lambda F')^{-1}R]$, where the prior mean ζ has little effect and the true data dominate the estimation of Θ.

4.3.1.5 Posterior distribution of Λ

The family level covariance matrix for *M* funds can be written as $\Lambda = I_M \otimes \lambda$. Only β and Θ are related to the variation of λ, and the covariance λ can be written as a combination of the diagonal matrix of standard deviations and a matrix of correlation, i.e. $\Xi\Phi\Xi$. Thus the joint distribution of Ξ and Φ can be stated as

$$\begin{aligned} P(\Xi,\Phi|\beta,X,\Theta) &\propto P(\beta|\Xi,\Phi,\Theta)P(\Xi)P(\Phi) \\ &= \mathcal{N}_{MK}(\beta|X\Theta,\Xi\Phi\Xi)\mathcal{W}^{-1}(\Phi|K_0,I)log\text{-}\mathcal{N}(\Xi|v,s^2) \end{aligned}$$

We firstly derive the posterior distribution of the unscaled matrix that determines the correlation, given the prior is $\Phi \sim \mathcal{W}^{-1}(K_0, I)$,

$$\begin{aligned} P(\Phi|\beta,\Xi) &\propto \prod_{j=1}^{M} N(\beta_j|X_j\Theta,\Xi\Phi\Xi)\mathcal{W}^{-1}(K_0,I) \\ &\propto |\Xi\Phi\Xi|^{-\frac{M}{2}} exp\left[-\frac{1}{2}trS_0(\Xi\Phi\Xi)^{-1}\right]|\Phi|^{\frac{K_0+K+1}{2}} exp\left[-\frac{1}{2}tr(I\Phi^{-1})\right] \\ &\propto |\Phi|^{\frac{(K_0+M)+K+1}{2}} exp\left[-\frac{1}{2}tr(\Xi^{-1}S_0\Xi^{-1}+I)\Phi^{-1}\right] \end{aligned}$$

Therefore, we can show that

$$\Phi|\beta,\Theta,\Xi,K_0,M \sim Scaled\text{-}\mathcal{W}^{-1}(K_0+M,\Xi^{-1}S_0\Xi^{-1}+I) \tag{4.8}$$

where $S_0 = \sum_{j=1}^{M}(\beta_j - x_j\Theta)(\beta_j - x_j\Theta)'$. For k^{th} factor in the learning model, its variance is $\xi_k^2\Phi_{kk}$, where Φ_{kk} is the k^{th} value on the diagonal of Φ. The posterior distribution on Ξ can be estimated by using the Metropolis-Hastings algorithm since the distribution function is not in a convenient form. Given $\Xi = diag(\xi_1,\ldots,\xi_K)$, its conditional posterior distribution function can be written as

$$P(\xi_k|\beta,\Phi) \propto \prod_{j=1}^{M}(\beta_{k,j}|\mu_{\beta_k},\sigma^2_{\beta_k})log\text{-}\mathcal{N}(\xi_k|v_k,s_k^2)$$

where[9]

$$\mu_{\beta_k} = E(\beta_k) + Cov(\beta_k,\beta_{\text{-}k})Var([\beta_{\text{-}k}])^{-1}(\beta_{\text{-}k} - E(\beta_{\text{-}k}))$$
$$\sigma^2_{\beta_k} = Var(\beta_k) - Cov(\beta_k,\beta_{\text{-}k})Var([\beta_{\text{-}k}])^{-1}Cov(\beta_k,\beta_{\text{-}k})$$

and the prior on ξ_k is given by $\xi_k \sim log\text{-}\mathcal{N}(v_k, s_k^2)$. We then use a log-normal distribution as the proposed distribution to simulate the target distribution with the acceptance rate over 44%.[10]

4.3.2 The non-learning and partial learning models

After deriving the general learning model, we then look at the difference between the non-learning model, the partial learning model and the general learning model. The non-learning model can be regarded as an evaluation model with independent prior belief, while the partial learning model considers dependent prior only on the fund alphas. Given the likelihood function Eq(4.1), we can derive the non-learning model for fund *j* as

$$R_j = \alpha_j + f_j\beta_j + u_j, \quad u_j \sim N(0,\sigma^2)$$

Then we can draw α_j given R_j, f_j and β_j, assuming σ^2 is drawn from another procedure. The posterior belief then follows:

9 Since λ is a $K \times K$ matrix, thus $[\beta_{\text{-}k}]$ indicates a matrix without the k^{th} element.

10 Similar argument can be found in, for example, Gelman and Hill (2007) and O'Malley and Zaslavsky (2008).

$$
\begin{aligned}
P(\alpha_j|R_{.j}, f, \beta_j, \sigma^2) &\propto \prod_{n=1}^{N_j} N(R_{.j}|\alpha_j + f\beta_j, \sigma^2) N(\alpha_j|\mu_j, \sigma_j^2) \\
&\propto exp\left\{ -\frac{1}{2\sigma_j^2}(\alpha_j - \mu_j)^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N_j}[\alpha_j - (R_{.j} - f\beta_j)]^2 \right\} \\
&\propto exp\left[-\frac{1}{2\tilde{\sigma}_\alpha^2}(\alpha_j - \tilde{\alpha}_j)^2 \right]
\end{aligned}
$$

where

$$
\begin{aligned}
\tilde{\alpha}_j &= (\frac{\mu_j}{\sigma_j^2} + \frac{S_0}{\sigma^2})(\frac{1}{\sigma_j^2} + \frac{N}{\sigma^2})^{-1} \\
\tilde{\sigma}_\alpha^2 &= (\frac{1}{\sigma_j^2} + \frac{N_j}{\sigma^2})^{-1} \\
S_0 &= \sum_{i=1}^{N_j}(R_{.j} - f\beta_j)
\end{aligned}
$$

and assuming that α_j follows a prior belief, $\alpha_j \sim N(\mu_j, \sigma_j^2)$, for fund *j*. Thus, each of the *M* funds in the fund family is denoted with independent prior beliefs. In the simulation of the non-learning model we denote a non-informative prior on the variance parameter of β_j, thus its posterior distribution is the OLS estimation. For the prior distribution on α, we denote prior beliefs independent of each other. Therefore, the non-learning model can be regarded as the no pooling model, with specific prior on each of the funds.

JS applies a hierarchical model with dependent prior on individual funds' α_j. Their model can therefore be regarded as a varying intercept model while the factor loadings of other market benchmarks are left without Bayesian treatment. Given the same likelihood function Eq(4.1), the prior belief of α_j states

$$\alpha_j \sim N(\mu_\alpha, \sigma_\alpha^2), \quad (j = 1, \ldots, M)$$

The posterior mean of α_j can be derived in the same fashion as the non-learning model:

$$\begin{aligned} P(\alpha_j | R_{.j}, f, \beta_j, \sigma^2) &\propto \prod_{n=1}^{N_j} N(R_{.j} | \alpha_j + f\beta_j, \sigma^2) N(\alpha_j | \mu_\alpha, \sigma_\alpha^2) \\ &\propto exp\left\{ -\frac{1}{2\sigma_\alpha^2}(\alpha_j - \mu_\alpha)^2 - \frac{1}{2\sigma^2} \sum_{i=1}^{N_j} [\alpha_j - (R_{.j} - f\beta_j)]^2 \right\} \\ &\propto exp\left[-\frac{1}{2\tilde{\sigma}_\alpha^2}(\alpha_j - \tilde{\alpha}_j)^2 \right] \end{aligned}$$

where

$$\begin{aligned} \tilde{\alpha}_j &= (\frac{\mu_\alpha}{\sigma_\alpha^2} + \frac{S_0}{\sigma^2})(\frac{1}{\sigma_\alpha^2} + \frac{N}{\sigma^2})^{-1} \\ \tilde{\sigma}_\alpha^2 &= (\frac{1}{\sigma_\alpha^2} + \frac{N_j}{\sigma^2})^{-1} \\ S_0 &= \sum_{i=1}^{N_j} (R_{.j} - f\beta_j) \end{aligned}$$

For the mean performance μ_α, we denote prior belief as $\mu_\alpha \sim N(m_\alpha, V_\alpha)$; thus the posterior belief of μ_α is given by

$$\begin{aligned} P(\mu_\alpha, \alpha, \sigma_\alpha^2, m_\alpha, V_\alpha) &\propto \prod_{j=1}^{M} N(\alpha_j, \sigma_\alpha^2) N(\mu_\alpha | m_\alpha, V_\alpha) \\ &\propto exp\left\{ -\frac{1}{2}\left[(\frac{M}{\sigma_\alpha^2} + \frac{1}{V_\alpha})\mu_\alpha^2 - 2\mu_\alpha(\frac{M\bar{\alpha}_j}{\sigma_\alpha^2} + \frac{m_\alpha}{V_\alpha}) \right] \right\} \\ &= exp\left[-\frac{1}{2\tilde{\sigma}_\alpha^2}(\mu_\alpha - \tilde{\mu}_\alpha)^2 \right] \end{aligned}$$

and we have $\mu_\alpha \sim N(\tilde{\mu}_\alpha, \tilde{\sigma}_\alpha^2)$, where

$$\tilde{\mu}_\alpha = (\frac{M\bar{\alpha}_j}{\sigma_\alpha^2} + \frac{m_\alpha}{V_\alpha})(\frac{M}{\sigma_\alpha^2} + \frac{1}{V_\alpha})^{-1}$$
$$\tilde{\sigma}_\alpha^2 = (\frac{M}{\sigma_\alpha^2} + \frac{1}{V_\alpha})^{-1}$$
$$\bar{\alpha}_j = \frac{1}{M}\sum_{j=1}^{M}\alpha_j$$

In the model derived above, for each fund *i*, a common prior belief is applied to all the *M* funds in the same fund family. Thus, the common prior can be viewed as the additional information on the mean performance of the entire fund family. In the simulation, we include a diffuse prior on μ_α, i.e. apply a large value on V_α to eliminate the influence from m_α. The precision parameter σ_α is given a prior belief following inverse χ^2 distribution. Since JS include no prior information on other pricing factors in addition to α_j, a diffuse prior is then denoted to each of the factor loadings to let them converge to the OLS estimations, which is similar with the settings considered by JS.[11]

4.3.3 Prior beliefs

In this section we discuss the prior distribution we use for drawing from the posterior distribution of the parameters in the learning model. Although there are several possible choices of prior beliefs on all unknown variables, we concentrate on the family level variance, Λ, since it is closely related to the cross-sectional variability within the fund family. In particular, a diffuse prior would allow the data to dominate

[11] JS rearrange Eq (1) to have $R_j - f\beta_j = \alpha_j + u_j$, and β_j is obtained directly from the OLS regression.

the posterior distribution, while contracted prior leads to a high degree of shrinkage.

We consider three log normal distributions as the prior belief on ξ_k. Figure 4.1 shows our first choice, $log(\xi_k) \sim N(-1,1)$. The prior mean is then centred at around 0.25 suggesting ξ_k has a variance over 0.0625, which is far beyond the actual value observed in the data. This highly informative prior maintains the degree of shrinkage at a low level for the reason shown in section 4.3.1.2, where extremely diffuse variance drives the posterior mean to approach the OLS estimation. Thus, prior belief provides no information in this case.

The second and third choices of prior belief are illustrated in Figure 4.2. The dashed line given by $log(\xi_k) \sim N(-5,1)$ is centred at 0.003, that is 9×10^{-6} for variance. This prior is chosen to represent a plausible actual prior of alphas across funds within the fund family, since it is close to the highest cross-sectional variance among alphas given by the data. But its long right tail also enables the prior to provide sufficient deviation from the mean. The third choice of prior is given by the solid line in Figure 4.2. It is centred at 2×10^{-5}, which can match the lowest between variability suggested by the data. Such a prior is expected to substantially increase the shrinkage toward the prior mean in order to address the situation where information is heavily shared within the fund family.

We also designate prior distribution to other parameters in the learning model. The prior on Θ is centred at zero, as we assume that no manager is found to have superior stock selection ability. This is consistent with the settings given by PS and JS. The prior on the correlation matrix Φ is given by an inverse Wishart distribution

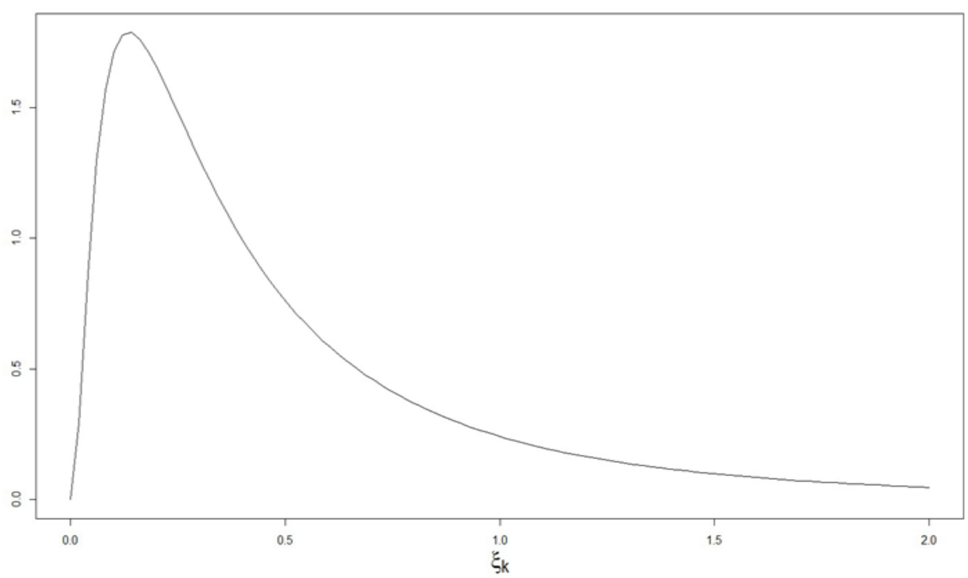

Figure 4.1 Prior distribution on ξ_k for $log(\xi_k) \sim N(-1,1)$

This figure illustrates the choice of the prior distribution considered for the cross-sectional variability parameter, ξ_k. Its logarithm value has a normal distribution with mean as -1 and variance as 1.

with a degree of freedom that is higher than the dimension of its scale matrix. This setting allows Φ to have a uniform prior distribution on the correlation parameters, since information regarding the correlation among family-level predictors is normally

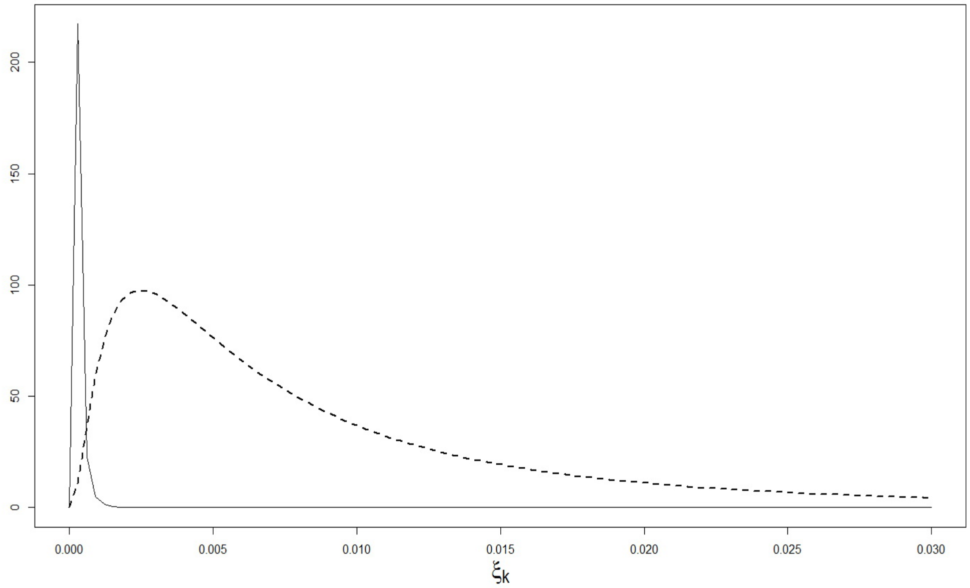

Figure 4.2 Prior distribution on ξ_k for $log(\xi_k) \sim N(-5,1)$ and $log(\xi_k) \sim N(-10,1)$

This figure illustrates the choice of the prior distribution considered for the cross-sectional variability parameter, ξ_k. The dashed line represents the distribution of $log(\xi_k) \sim N(-5,1)$, while the solid line is for $\log(\xi_k) \sim N(-10,1)$.

unknown by assumption. Moreover, the prior settings for the correlation matrix and the standard deviation for the k^{th} pricing factor considered in our research are different from those discussed in Barnard et al. (2000), where the group-level covariance matrix is decomposed into product of the correlation matrix and the diagonal matrix of standard deviations. Then a certain prior can be allocated on the particular predictor with a marginal uniform prior on the correlation parameters. But our technique can achieve the same objective with simpler computation and faster convergence.

4.4 Simulation analysis

4.4.1 Simulation with returns of hypothetical fund family

In this section we report the simulation results of the learning models under the various prior beliefs chosen in section 4.3.3. We conduct the simulations based on hypothetical returns generated by different compositions of the benchmark. For the CAPM model, the abnormal performance α is assumed to have a normal distribution with mean of 7.1×10^{-4} and standard deviation of 2.23×10^{-3}; and β_{market} has a normal distribution with a mean value of 0.979 and standard deviation of 0.087. The standard deviation of the error term follows $log(\sigma) \sim N(-4.044, 0.398^2)$. The 3-factor model α follows a normal distribution with a mean of 0.0767% and standard deviation of 0.226, and β_{market} follows $N(1.0293, 0.122^2)$, while β_{hml} and β_{smb} follow $N(-0.036, 0.093^2)$ and $N(0.053, 0.086^2)$, respectively. The residual standard deviation has $log(\sigma) \sim N(-4.079, 0.378^2)$. For the 4-factor model, α is drawn from a normal distribution with mean of 0.0806% and standard deviation of 0.231%, and β_{market} is assumed to follow $N(1.029, 0.121^2)$.

The other pricing factors are drawn independently from the following distribution: $\beta_{hml} \sim N(-0.037, 0.093^2)$, $\beta_{smb} \sim N(0.0523, 0.0844^2)$, $\beta_{mom} \sim N(0.006, 0.017^2)$. The standard deviation of the error term $log(\sigma)$ is drawn from the log-normal distributed with $N(-4.086, 0.376^2)$. The returns and pricing factors are then drawn independently of each other to form returns for a particular fund.

Table 4.1 reports the posterior simulations from three types of learning model under the chosen prior beliefs using hypothetical fund returns. All the three types of learning model exhibit a substantial degree of shrinkage with a rapid decrease in dispersion of the cross-sectional variability in funds' α; that is, λ_{α} declines sharply under the chosen prior beliefs. The results from the general learning model seem to have the highest degree of shrinkage, since the λ_{α} in Panel C is lower than those in Panel A by over 60 basis points and lower than the partial learning model by almost 90 basis points under the high scepticism prior. It is also worth noting that the degree of shrinkage decreases considerably across the prior beliefs when using both the partial learning model and the non-learning model. Specifically, λ_{α} from the CAPM model drops by almost 1000 basis points in Panel B, from 0.1234 to 0.0101, while it behaves more stably in Panel C with only an 80-basis point change. The general learning model incorporates the prior belief on the variance from both the pricing factors and it also works as the scale factor in the denominator of the posterior mean, thus the prior belief is more likely to have significant influence on the cross-sectional variability of fund alphas.

Figures 4.3, 4.4 and 4.5 provide further evidence to confirm the shrinkage. Figure 4.3 illustrates the boxplot of the posterior mean of the α for the 5 hypothetical funds. The value is quite dispersed when $\log(\xi_k)$ has a diffuse prior, and the median of each α's posterior distribution is close to the OLS estimates since a highly close-diffuse prior would mitigate the influence from the prior mean. The dispersion on α reduces significantly when turning to a less diffuse prior. In the extreme case where $\log(\xi_k)$ has the high scepticism prior, the funds' α converges to a common mean which is close to zero. There is also some evidence supporting the notion that the shrinkage is sensitive to the evaluation model chosen. The boxplot shown in Figure 4.4 suggests that the α estimated by the 3-factor model has a low degree of shrinkage under all three prior beliefs compared to those from the CAPM. Similar results can also be found in Figure 4.5 where the 4-factor model is considered.

Table 4.1 also reports the results of the mean performance for a particular fund family, θ_α. As shown in Section 4.2.1.4, the posterior mean of θ_α is weighted by both the OLS estimates and prior information. Since we apply no predictors at the family level likelihood, Eq(4.2), X_j is assumed to be an identity matrix for all *M* funds. Thus Eq(4.2) is by design a sum of family's mean performance and the fund's idiosyncratic performance. In the case where Λ has diffuse prior beliefs on its diagonal, each of the elements in β should converge to its OLS estimates. On the other hand, when a least dispersed prior is considered for Λ, β should reduce to its mean, Θ. We therefore expect the factor loadings and the α within the same family to converge to a common mean which can be attributed as the mean performance of the fund family. One may argue that the fund manager can also contribute to the mean performance; thus a feasible extension to the general learning model is to further decompose the mean value Θ and to designate particular predictors representing the difference between the contribution from the manager and that from the fund family.

Table 4.1 Simulation of learning within fund family

	CAPM			3-factor model			4-factor model		
Prior Beliefs	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
Panel A				*Non-learning model*					
λ_α	0.0969	0.0574	0.0092	0.0858	0.0411	0.0077	0.0927	0.0529	0.0079
σ_R	0.0157	0.0157	0.0159	0.0194	0.0194	0.0194	0.0168	0.0168	0.0169
Panel B				*Partial learning model*					
λ_α	0.1234	0.0631	0.0101	0.1117	0.0434	0.0076	0.1169	0.0515	0.0079
θ_α	0.0003	0.0001	0.0000	0.0007	0.0008	0.0008	0.0017	0.0017	0.0015
σ_R	0.0157	0.0157	0.0159	0.0194	0.0194	0.0194	0.0167	0.0168	0.0168
Panel C				*General learning model*					
λ_α	0.0082	0.0034	0.0001	0.0058	0.0012	0.0001	0.0069	0.0017	0.0001
θ_α	0.0001	0.0001	0.0002	0.0007	0.0008	0.0004	0.0017	0.0017	0.0008
σ_R	0.0157	0.0157	0.0159	0.0194	0.0194	0.0194	0.0168	0.0168	0.0169

Notes: This table presents the simulation results from three evaluation models: the non-learning model, the partial learning model and the general learning model. The posterior mean of the variables, i.e. the in-family variability λ_α, the family level mean performance θ_α, and the fund's individual risk level σ_R, are reported. We control the prior belief on the scaled parameter of the cross-sectional variability in α, ξ_α to be three distinct distributions, i.e. diffuse prior, $log(\xi_\alpha) \sim N(-1,1)$; low scepticism, $log(\xi_\alpha) \sim N(-5,1)$ and high scepticism, $log(\xi_\alpha) \sim N(-10,1)$. The prior belief on the mean value of the k^{th} pricing factor, θ_k, is centred at zero with a diffuse variance. The scaled parameter of θ_β is also assumed to have a diffuse distribution. Panels A, B and C report the simulation results from the CAPM, Fama French 3-factor model and the 4-factor model. The posterior distributions of the variables considered are simulated by the MCMC technique by using hypothetical returns from 5 funds. The fund returns are generated through Eq(4.1), in which the factor loadings and the market benchmarks are drawn independently across funds. The distribution parameters are chosen to match the empirical results.

The posterior mean of θ_α reported in Table 4.1 seems to be very close to zero across all the learning models considered. The results document some weak support for a decreasing pattern of the value of θ_α with a diminishing dispersion on the prior variance, i.e. it reduces from 0.17% to 0.08% when the general learning model based on the 4-factor model is considered. The value is even lower when using a CAPM based partial learning model. This may be explained with the aid of Figure 4.3, in which the posterior α of each fund is more concentrated around zero and the extreme values at both ends offset each other. The distribution of each fund's α in Figure 4.4 has a more extreme value at the positive end, implying a more positive θ_α in a 3-factor based learning model. A similar situation can be found in Figure 4.5, where the 4-factor based learning model is considered, i.e. the median of the posterior α is further from zero compared to the others. Consequently, θ_α provides additional information on the common performance across funds within the same fund family. Our simulation results suggest that the abnormal performance can be attributed mainly to funds' idiosyncratic behaviour, since the common mean reduces to zero under the least dispersed prior.

Figure 4.6 illustrates the posterior mean of market beta in the general learning model. Since we put non-informative prior on β, its posterior mean is expected to converge to the OLS estimates. The boxplot in Figure 4.6 shows a steady shrinkage across the chosen prior beliefs. We further extend the simulation to incorporate the influence of informative prior beliefs on other pricing factors. Table 4.3 shows the results.

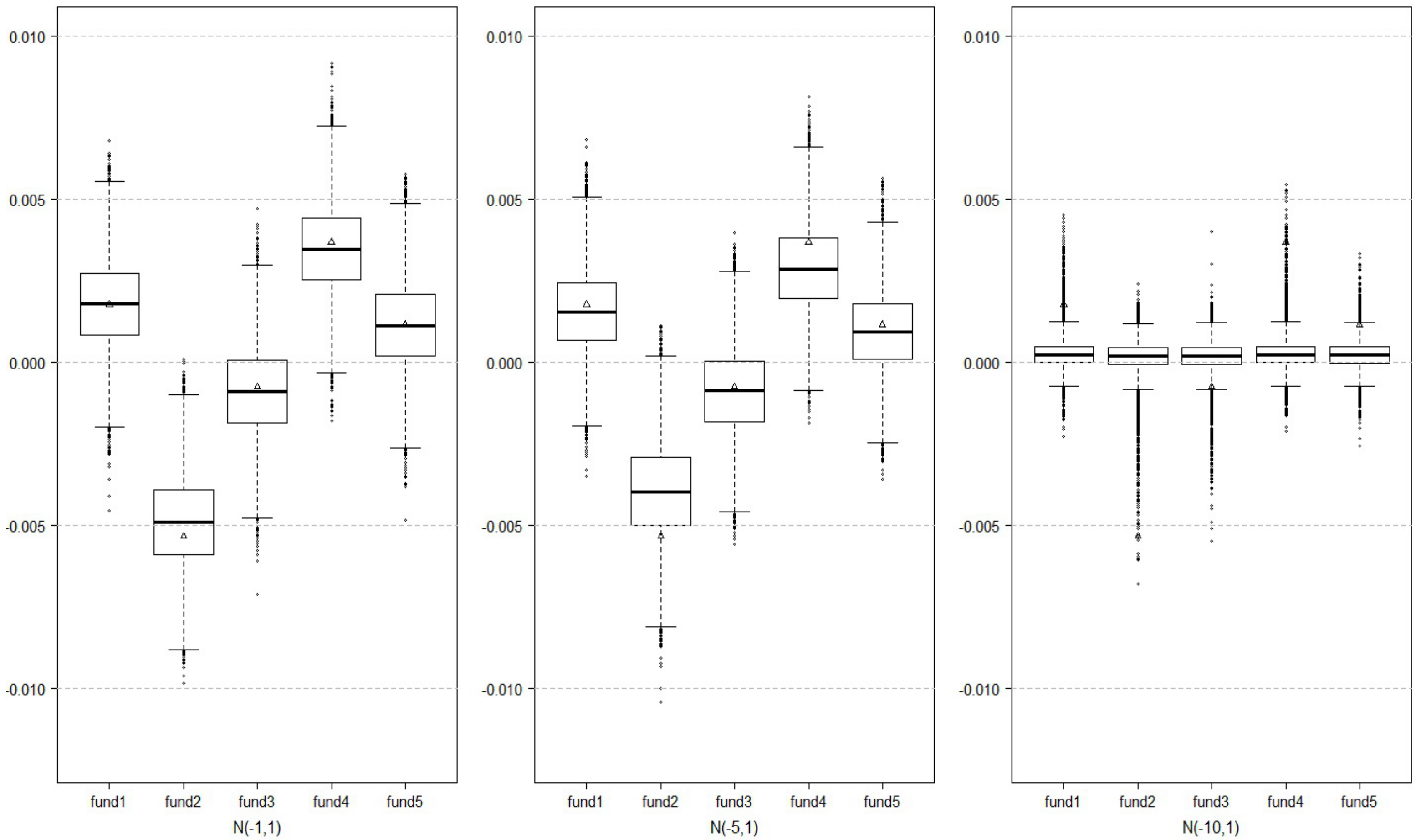

Figure 4.3 Boxplot of Posterior Draws of CAPM α

Notes: This figure illustrates 6000 posterior draws from 5 hypothetical funds' α given the decreasingly dispersed prior beliefs on Λ in the CAPM formed general learning model.

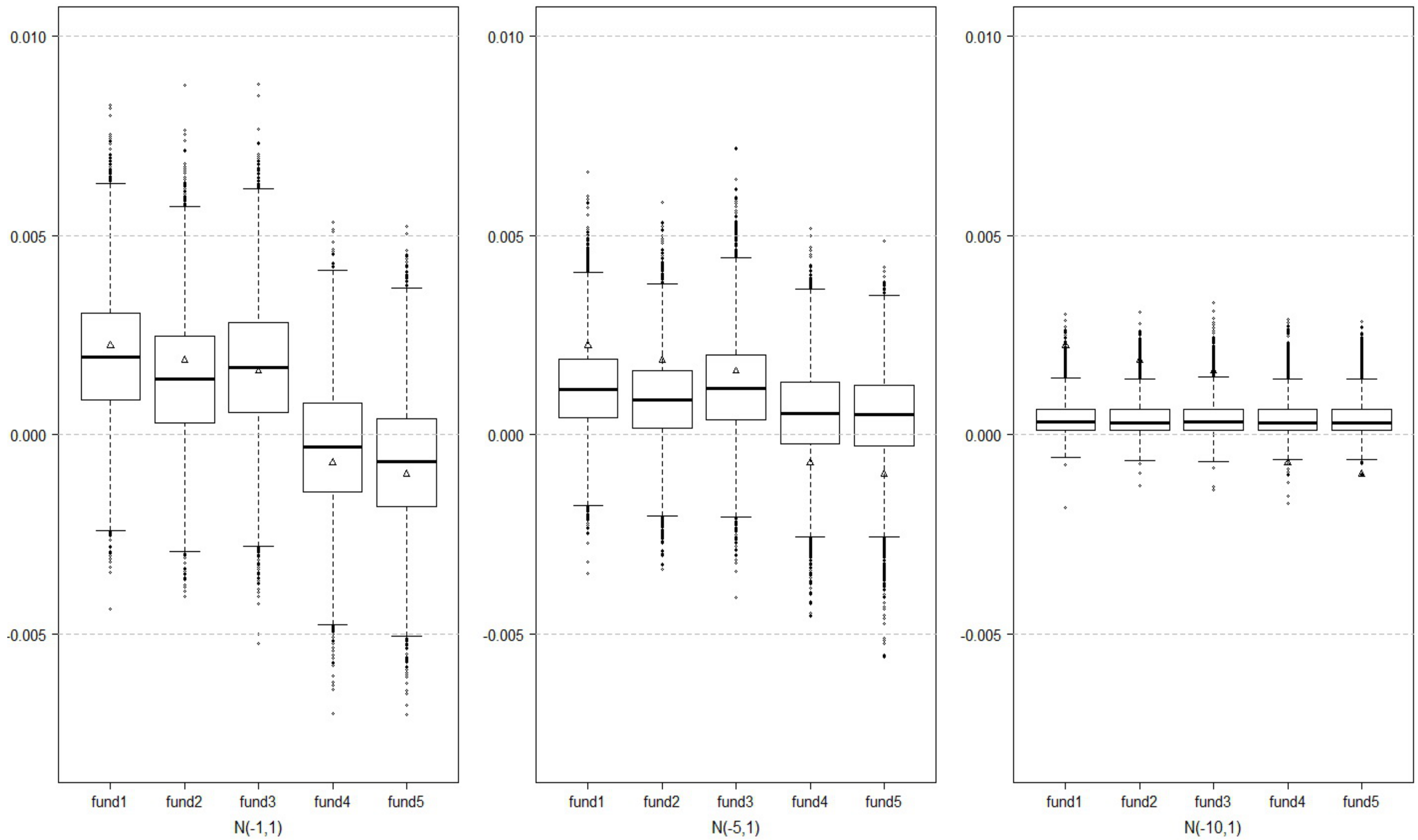

Figure 4.4 Boxplot of Posterior Draws of 3-factor model α

Notes: This figure illustrates 6000 posterior draws from the 5 hypothetical funds' α given the decreasingly dispersed prior beliefs on Λ in the 3-factor based general learning model.

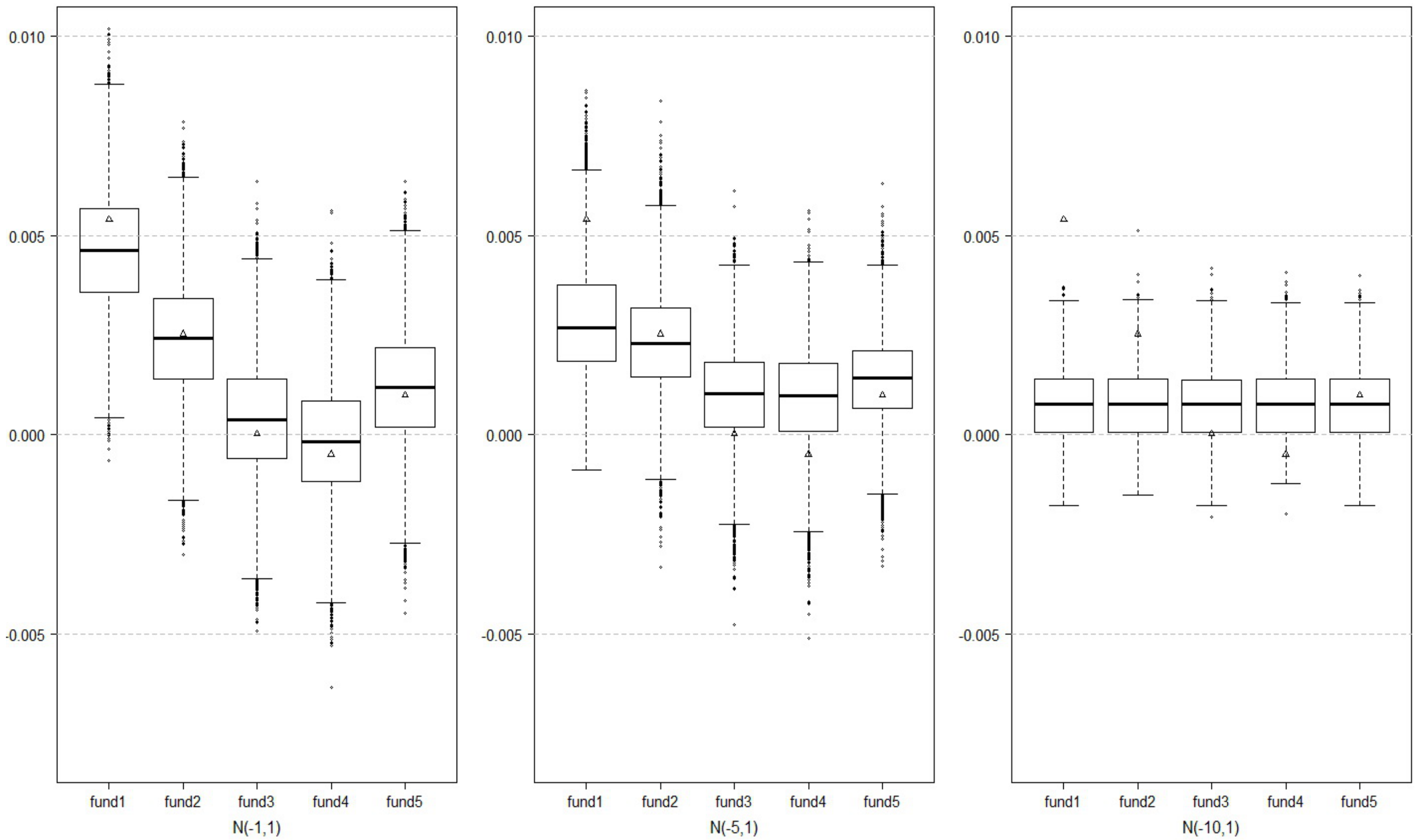

Figure 4.5 Boxplot of Posterior Draws of 4-factor model α

Notes: This figure illustrates 6000 posterior draws from 5 hypothetical funds' α given the decreasingly dispersed prior beliefs on Λ in the 4-factor based general learning model.

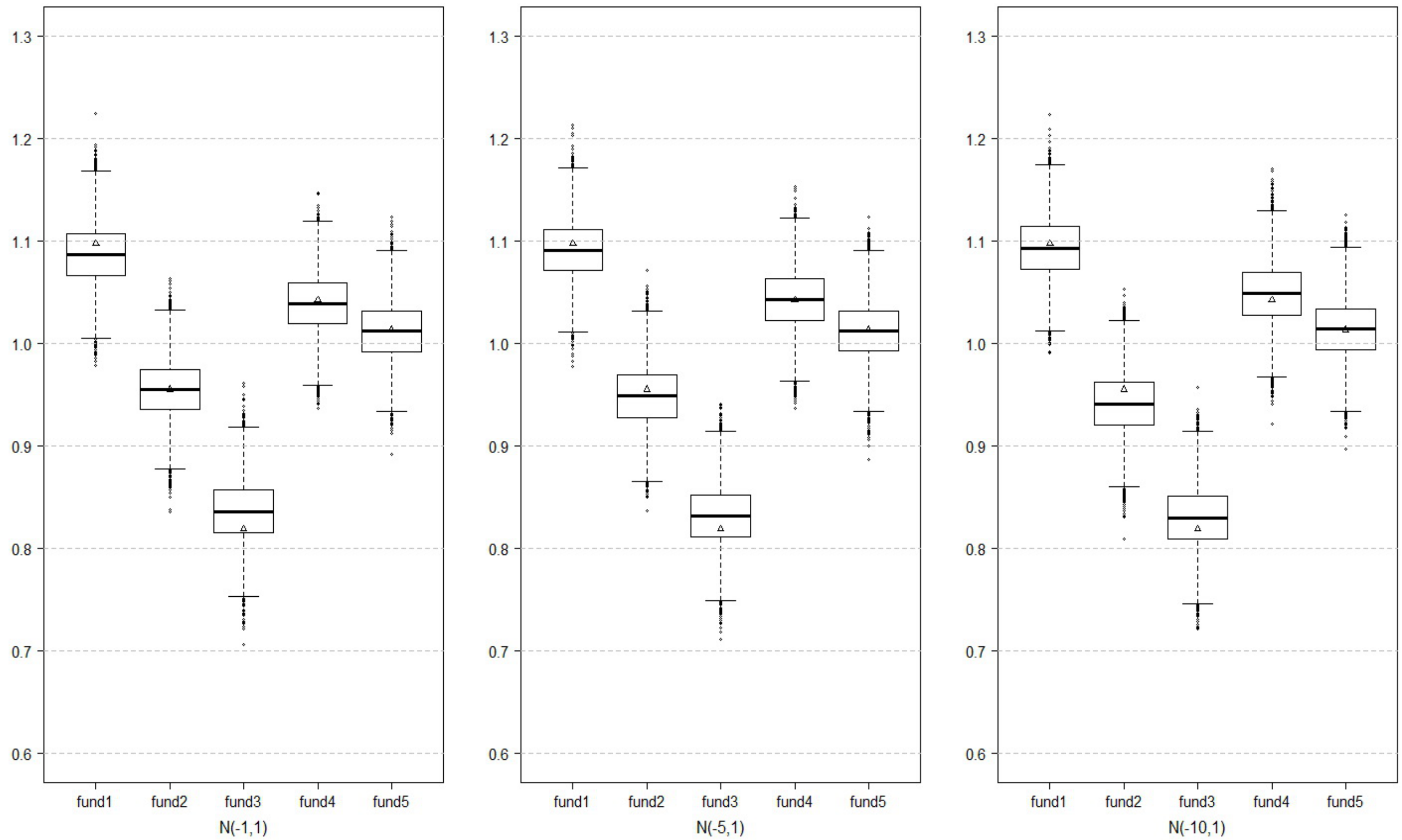

Figure 4.6 Boxplot of Posterior Draws of CAPM β_{market}

Notes: This figure illustrates 6000 posterior draws from 5 hypothetical fund's β_{market} given the decreasingly dispersed prior beliefs on Λ in the CAPM formed general learning model.

4.4.2 Simulation with returns of hypothetical funds universe

We consider a more extreme case where, instead of considering a hypothetical family with 5 funds, we enlarge the sample size to incorporate 200 funds to analyse the degree of shrinkage of funds' α. Results are reported in Table 4.2. The posterior mean of δ_α suggests that of the three models, the general learning model exhibits the highest degree of shrinkage of funds' α, which is consistent with the results reported in Table 4.1. The posterior means of λ_α given by the non-learning and the partial learning models have a similar value under the same prior. Moreover, compared to the results in Table 4.1, simulations with a larger group of funds produces smaller value of λ_α for a given prior, indicating that it becomes easier to converge to the common mean when they are able to gain information from more funds. However, there is only weak evidence to support the declining pattern of λ_α with less dispersed prior beliefs. This is because the growing sample size may lead to more heterogeneous beliefs among individual funds' α, which therefore slows down the efficiency of the convergence process.

The posterior means of θ_α reported in Panels A and B are higher than those in Table 4.1. Meanwhile, we find that funds' idiosyncratic performance seems to have limited impact on the overall mean performance, since θ_α remains almost unchanged across different prior beliefs from both the partial learning and the general learning models. This implies that managers' superior (inferior) performances offset each other in a large funds population, and such mean performance is also independent of the prior information. The steady nature of θ_α documented in Panel B is apparently different from that discovered by JS. This is because we only incorporate prior beliefs in the cross-sectional variability, and leave the prior on β non-informative, whereas JS put decreasingly dispersed prior on the group mean, and find that the posterior mean is driven toward zero.

Figure 4.7 plots the density of the posterior mean of the 200 funds' α with respect to the chosen prior beliefs. Not surprisingly, the solid line, which indicates the density of α given a close-diffuse prior, has the lowest degree of kurtosis among the three densities, while the dashed line has more values around its mean. However, Figure 4.7 shows there is a limited margin on the shrinkage level between different prior beliefs, which is consistent with the results found in λ_α in Table 4.2. Furthermore, it seems that more funds are found to have a positive α given a left skewed density no matter which prior belief is chosen. Our results in relation to the simulation of returns of hypothetical fund universe suggest a low degree of shrinkage of the cross-sectional α compared to that found in fund families. But a steady mean performance, θ_α, implies a feasible estimate of the mean performance for the fund universe through the general learning model.

Table 4.2 Simulation of learning across funds universe

	CAPM			3-factor model			4-factor model		
Prior Beliefs	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
Panel A				*Non- learning model*					
λ_α	0.0502	0.0496	0.0488	0.0495	0.0489	0.0482	0.0519	0.0514	0.0506
σ_R	0.0211	0.0211	0.0211	0.0189	0.0189	0.0189	0.0186	0.0186	0.0186
Panel B				*Partial learning model*					
λ_α	0.0500	0.0493	0.0484	0.0479	0.0473	0.0466	0.0498	0.0492	0.0484
θ_α	0.0004	0.0004	0.0004	0.0009	0.0009	0.0009	0.0011	0.0011	0.0011
σ_R	0.0211	0.0211	0.0211	0.0189	0.0189	0.0189	0.0186	0.0186	0.0186
Panel C				*General learning model*					
λ_α	0.0025	0.0024	0.0024	0.0023	0.0022	0.0022	0.0025	0.0024	0.0024
θ_α	0.0004	0.0004	0.0004	0.0009	0.0009	0.0009	0.0011	0.0011	0.0011
σ_R	0.0211	0.0211	0.0211	0.0189	0.0189	0.0189	0.0186	0.0186	0.0186

Notes: This table presents the simulation results from three evaluation models: the non-learning model, the partial learning model and the general learning model. The posterior mean of the variables, i.e. the in-family variability λ_α, the family level mean performance θ_α, and the fund's individual risk level σ_R are reported. We control the prior beliefs on the scaled parameter of the cross-sectional variability in α, and assume three distinct distributions for ξ_α, i.e. diffuse prior, $log(\xi_\alpha) \sim N(-1,1)$; low scepticism, $log(\xi_\alpha) \sim N(-5,1)$ and high scepticism, $log(\xi_\alpha) \sim N(-10,1)$. The prior beliefs in the mean value of the k^{th} pricing factor, θ_k, are centred at zero with a diffuse variance. The scaled parameter of θ_β is also assumed to have a diffuse distribution. Panels A, B and C report the simulation results from the CAPM, the 3-factor and the 4-factor models. The posterior distributions of the variables considered are simulated using the MCMC technique based on hypothetical returns of 200 funds. The fund returns are generated through Eq(4.1), in which the factor loadings and the market benchmarks are drawn independently across funds. The distribution parameters are chosen to match the empirical results.

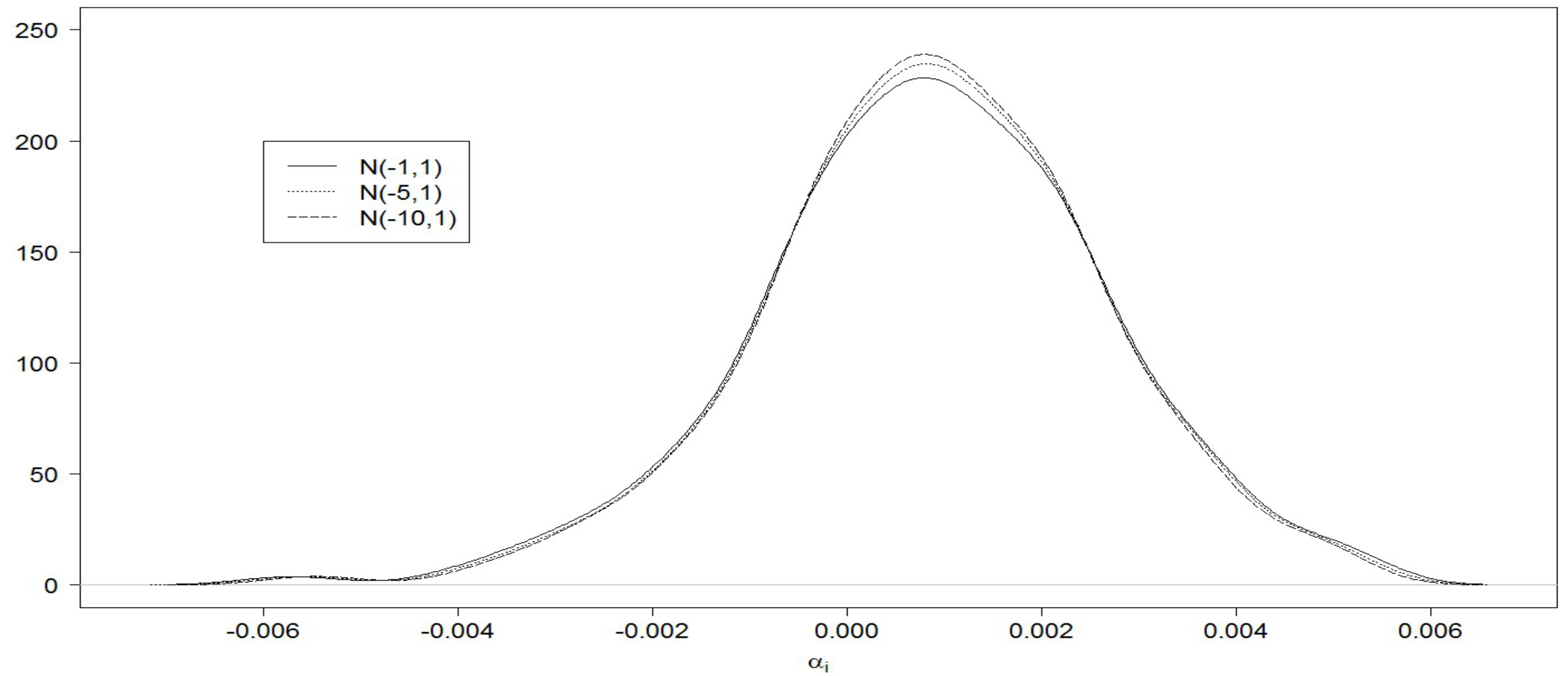

Figure 4.7 Density of the posterior draws of CAPM α

This figure illustrates 6000 posterior draws from the CAPM α by applying the general learning model to the hypothetical fund population with decreasingly dispersed prior beliefs on Λ.

The general learning model enables us to consider specific prior beliefs on factor loadings. Using this property, we further extend our simulation to allocate information on all of the elements in β in addition to α. In other words, the factor loadings of each market benchmark in a particular pricing model are assumed with informative prior beliefs before undertaking the estimation. Table 4.3 reports the results.

We find that the chosen prior belief on other pricing factors can influence the posterior dispersion of α. For example, the posterior mean of λ_α increases from 0.035% to 0.118% when the prior belief on k^{th} pricing factors turns to a dispersed one. This finding is also consistent when different pricing model is considered. From the fund family's perspective, if investors are only certain that funds in the same family have similar risk exposure to the market benchmarks, they may choose more concentrated prior beliefs on the corresponding factor loadings. On the other hand, investors might have limited knowledge on the overall skill of the fund family, and hence they choose a more dispersed prior belief on α. Such a situation can be represented by column 3 of Table 4.3 under the settings of CAPM. The results imply a slightly lower degree of shrinkage of λ_α relative to those reported in Panel C of Table 4.1, indicating that adding prior information from other pricing benchmarks can improve the shrinkage of the α value. In other words, if the prior information considered happens to be correct, the general learning model can provide a more precise estimation of the cross-sectional mean performance of the family. Intuitively, the situation discussed above could be a more common case in reality. Since fund companies publish their top holdings frequently, investors are more likely to form their own opinions on the co-movements between the fund and the market portfolio. Hence, a less dispersed prior can be used to represent the investors' belief before seeing the data. However, it is often the case that the manager's stock selection skill is unknown to the investors. Therefore a diffuse prior on α could be a reasonable setting.

Moreover, we consider another extreme situation, in which investors are more convinced that the fund family contains no skilled managers, but they are also unsure that the market benchmark can completely price the fund return. Therefore, a highly concentrated prior is defined on both the α and the market beta. Such a scenario is considered in the second column of the CAPM settings. The result shows a significant degree of shrinkage of the cross-sectional market beta as λ_β decreases with less dispersed priors than that in the fourth column. However, compared with the results on λ_α given by Panel C of Table 4.1, where market beta has a diffuse prior, we find that λ_α increases by over 10 bps. This is because the general learning model provides a compromise estimation of λ_α between the real data and the prior belief, since the hypothetical returns still contain evidence to support the existence of skilful managers. Thus, the posterior cross-sectional variability on α increases to signal such concerns.[12]

[12] Unlike the hypothetical returns generated by JS, in which the abnormal return has been centered to have a

In Table 4.4, we look further into the non-equal prior problem by computing the posterior correlation coefficients of the parameters considered in Table 4.3. In general the correlation between the different pricing factors and the abnormal returns remains at a low level. However, this does not contradict the results found in Table 4.3, since we place only a diffuse prior on the correlation matrix of all the pricing factors. It is not only the correlation coefficient but also the cross-sectional variability of a certain pricing factor that can decide the learning outcome. Therefore, such low correlation coefficient can suggest a low level of cross-fund learning only in the correlation itself. Our method provides a way to define an informative prior on the correlation matrix. However, the construction of an efficient prior remains an open question in the statistics literature.

zero mean, we draw the abnormal returns from $N(0.071\%, 0.223\%^2)$, which matches the general empirical findings in the real fund industry.

Table 4.3 Simulation of learning across funds with non-equal prior

	CAPM			3-factor model			4-factor model		
α prior	$N(-10,1)$	$N(-1,1)$	$N(-10,1)$	$N(-10,1)$	$N(-1,1)$	$N(-10,1)$	$N(-10,1)$	$N(-1,1)$	$N(-10,1)$
k^{th} prior	$N(-10,1)$	$N(-10,1)$	$N(-5,1)$	$N(-10,1)$	$N(-10,1)$	$N(-5,1)$	$N(-10,1)$	$N(-10,1)$	$N(-5,1)$
λ_α	0.0012	0.0078	0.0004	0.0009	0.0055	0.0002	0.0006	0.0060	0.0002
λ_β	0.0926	0.0861	0.0981	0.0313	0.0268	0.0562	0.1465	0.1425	0.1531
θ_α	0.0002	0.0000	0.0000	-0.0005	0.0006	0.0002	0.0010	0.0016	0.0010
θ_β	0.9803	0.9804	0.9839	1.0161	1.0037	1.0085	1.1009	1.0938	1.0972
λ_{HML}	-	-	-	0.0235	0.0473	0.0525	0.0021	0.0009	0.0223
λ_{SMB}	-	-	-	0.1116	0.1081	0.1045	0.0547	0.0319	0.0630
θ_{HML}	-	-	-	-0.0456	-0.0639	-0.1376	-0.0015	0.0002	-0.0152
θ_{SMB}	-	-	-	0.0287	0.0870	0.0925	0.0488	0.0643	0.0681
λ_{MOM}	-	-	-	-	-	-	0.0010	0.0007	0.0080
θ_{MOM}	-	-	-	-	-	-	0.0012	-0.0002	-0.0025

Notes: This table presents the simulation results from the general learning model. The posterior mean of the variables, i.e. the in-family variability on all the pricing factors, λ, and the mean performance of all the pricing factors, θ, are reported. We control the prior belief on the scaled parameters of the cross-sectional variability in factor loadings, ξ_k. The prior beliefs on the mean value of the k_{th} pricing factor, θ_k, are centred at 1 with various prior beliefs. We report results based on three pricing models: CAPM, the 3-factor and the 4-factor models. The posterior distributions of the variables considered are simulated by the MCMC technique by using hypothetical returns of 5 funds. The fund returns are generated through equation 1, in which the factor loadings and the market benchmarks are drawn independently across funds. The distribution parameters are chosen to match the empirical results.

Table 4.4 Posterior correlation coefficients

	CAPM			3-factor model			4-factor model		
α prior	$N(-1,1)$	$N(-1,1)$	$N(-10,1)$	$N(-1,1)$	$N(-1,1)$	$N(-10,1)$	$N(-1,1)$	$N(-1,1)$	$N(-10,1)$
k^{th} prior	$N(-1,1)$	$N(-10,1)$	$N(-5,1)$	$N(-1,1)$	$N(-10,1)$	$N(-5,1)$	$N(-1,1)$	$N(-10,1)$	$N(-5,1)$
$\rho_{\alpha,\beta}$	0.1924	0.2578	0.1700	0.0113	-0.0637	0.0224	-0.0764	-0.0936	-0.0236
$\rho_{\alpha,HML}$	-	-	-	0.0807	0.0685	-0.0795	-0.0108	0.0113	-0.0727
$\rho_{\alpha,SMB}$	-	-	-	0.1000	0.1711	-0.0902	0.0863	0.0673	0.0366
$\rho_{\alpha,MOM}$	-	-	-	-	-	-	0.1111	0.0334	0.0427

Notes: This table reports the posterior correlation coefficients from the general learning model. We control the prior belief on the scaled parameters of the cross-sectional variability in factor loadings, ξ_k. The prior beliefs on the mean value of the k^{th} pricing factor, θ_k, are centred at 1 with various prior beliefs. We report results based on three pricing models: CAPM, the 3-factor and the 4-factor models. The posterior distributions of the variables considered are simulated by the MCMC technique by using hypothetical returns of 5 funds. The fund returns are generated through equation 1, in which the factor loadings and the market benchmarks are drawn independently across funds. The distribution parameters are chosen to match the empirical results.

4.4.3 Simulation with the universe of real funds

In this section, we consider the simulation using the returns from the actual mutual funds. We select monthly returns of 220 unit trusts from 47 fund families in the UK fund industry from 2001 to 2010. All the sampled funds are UK equity unit trusts. We screen out the non-equity funds and the mixed funds since our performance evaluation focuses only on fund managers' stock selection skill. Within each of the fund families, we also screen out the new funds due to splitting and keep funds with longest return history for each share class. To focus solely on the domestic funds, the funds in our sample are all UK domicile equity funds, indicating that most of their capital should be invested in UK companies. Meanwhile, the UK domicile funds share the similar market benchmarks, which facilitate estimation of the funds' alphas by the factor models.

We employ three sets of benchmark returns to form the baseline performance evaluation model. We choose the FTSE All Shares as the excess market return factor motivated by CAPM. The returns of the additional size and book to market factors in the Fama French 3-factor model are computed by two pairs of market portfolios: the size factor is generated by the difference between the FTSE 100 index and the FTSE small capital index; the book to market factor is calculated by taking the difference between the MSCI UK Growth index and the MSCI UK Value index. The returns of the additional momentum factor in the 4-factor model are generated by using the 1-year high return portfolio minus the low return portfolio.

Firstly, in Table 4.5 we consider the situation in which informative prior beliefs are only given to the within variability of the cross-sectional alphas, δ_{α}. In other words, the investors are presumed to have prior information on how individual alphas deviate from each other within the same fund family, which is similar with the settings considered in the fake data simulation. We include the simulation results given by the non-learning model with independent prior beliefs, the partial learning model with dependent prior beliefs only on funds' alphas, and the general learning model, which we design to provide a full Bayesian treatment on each of the pricing factors. For each type of learning model, we conduct the simulation through three different baseline evaluation models, i.e. CAPM, 3-factor model and 4-factor model. The prior beliefs selected for λ_{α} are the same as those implemented in the fake data simulation. In addition, since no information is given on the mean performance of the fund family or on the family mean value of other pricing factors, we apply a diffuse prior distribution on the prior variance of θ_{α}, θ_{β}, θ_{HML}, θ_{SMB} and θ_{MOM}, and the prior means are centred at 0. The scale parameters on each of the pricing factors, except those on θ_{α}, all have diffuse priors.

The posterior mean of λ_{α}, which indicates how individual funds deviate from the family mean, decrease rapidly with the increase in scepticism on both the skill level and the within variation. Compared with the value of λ_{α} from the non-learning and partial learning models, the general learning model seems to be more sensitive to the priors chosen. λ_{α} in the partial learning model is about 20 basis points higher than that from the general learning model under the low scepticism prior. The difference is even larger under the diffuse prior, but they all turn to zero when a high scepticism prior is given. The results in Table 4.5 also suggest that such a decreasing pattern is not sensitive to the model specification, since the difference in magnitude is robust in all the types of baseline evaluation models.

The posterior mean of the family mean performance θ_α, and individual funds' alphas reported by Panels B and C of Table 4.5, also experience a decrease in value with the increasing scepticism in the prior beliefs, indicating that the prior information on family's mean performance would alter investors' view of individual funds' performance. Particularly, the funds' alphas reduce to θ_α when the high scepticism prior belief is applied, because λ_α approaches 0 under the least dispersed variance and the cross-sectional variation among alphas is almost eliminated within the same fund family. Although the prior mean of θ_α is centred at 0, its diffuse prior variance mitigates the influence from the prior mean and allows the real data to dominate the posterior distribution of θ_α. Meanwhile, Table 4.5 also provides some evidence to support the presence of managers' skill. By the assumption of the general learning model, the difference between θ_α and alphas under the diffuse and low scepticism priors can be regarded as the gain from funds' cross-sectional variation. Panels B and C both document that the funds' average alphas exceed θ_α for more than 20 basis points under the diffuse and low scepticism priors for all types of baseline evaluation model. However, since we provide no further decomposition on the family mean performance, we presume that apart from the fund families, θ_α might still incorporate a contribution by individual fund managers. But such a portion in θ_α should be limited, since for each fund family we keep only one fund for each share class, in order to maintain the variety of funds with distinct investment objectives in a fund family. One may argue that θ_α should maintain a stable value instead of decreasing with the scepticism prior. Since Eq(4.7) suggests that the posterior belief of Θ is a weighted average of prior information and the real data, the posterior mean of Θ is conditional only on the posterior distribution of the in-family covariance matrix Λ when $\Delta^{-1} \to 0$. Thus, the posterior mean of Θ may also shift with the changing value of the prior belief. However, given a high scepticism prior the prior variance approaches zero, and can hardly affect Θ, which drives the average alpha to θ_α.

Baks (2003) provides an alternative way to extract the family contribution out of funds' individual alphas through a Cobb-Douglas production function by denoting arbitrary weights on the performance of managers and fund organisations, respectively. The performance attribution is therefore sensitive to the weights chosen. Moreover, we are not surprised to see that the posterior means of β and θ_β documented in Table 4.5 remain almost unchanged, since no informative prior beliefs are applied to both θ_β and λ_β throughout the simulation.

We further investigate how prior information from other pricing factors affects the posterior distribution of the cross-sectional alphas and θ_α, by placing prior beliefs simultaneously on θ_α and the family mean and the scale parameters of all the other pricing factors. This is also an important feature of the general learning model, given that it enables us to denote specific prior beliefs on each of the pricing factors in the baseline evaluation model. The priors on the scale parameters are similar to those discussed in Table 4.5. The family mean value of each of the pricing factors (including θ_α) are also assigned with prior beliefs to address the learning issue, i.e. the k^{th} element in vector Θ is set to have $\theta_k \sim (0, 100)$ as the diffuse prior; for the low scepticism prior we set $\theta_k \sim (0, 1)$; for the high scepticism prior we have $\theta_k \sim (0, 0.001)$. Table 6 reports the posterior results of the parameters of interest.

Table 4.5 Simulation of learning within fund family

	CAPM			3-factor model			4-factor model		
Prior belief	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
Panel A				*Non-learning model*					
$\alpha(\%)$	0.7821	0.5121	-0.0404	0.8539	0.5921	-0.0379	0.9035	0.6369	-0.0354
β	0.9768	0.9768	0.9772	1.0252	1.0248	1.0246	1.0254	1.0251	1.0253
λ_α	0.1422	0.0500	0.0077	0.1422	0.0500	0.0082	0.1421	0.0500	0.0081
Panel B				*Partial learning model*					
$\alpha(\%)$	0.8384	0.8351	0.1557	0.9134	0.9091	-0.0500	0.9613	0.9609	0.2225
β	0.9768	0.9774	0.9713	1.0252	1.0254	1.0253	1.0245	1.0254	1.0213
$\theta_\alpha(\%)$	0.6182	0.5193	0.1557	0.6575	0.5065	-0.0501	0.9826	0.9633	0.2225
λ_α	0.2101	0.0515	0.0077	0.2111	0.0526	0.0081	0.2113	0.0532	0.0075
Panel C				*General learning model*					
$\alpha(\%)$	0.8446	0.8367	0.4947	0.9134	0.9043	0.4075	0.9665	0.9731	0.5032
β	0.9772	0.9771	0.9769	1.0248	1.0254	1.0252	1.0248	1.0247	1.0247
$\theta_\alpha(\%)$	0.7042	0.6363	0.4953	0.6712	0.5381	0.4081	0.7657	0.6736	0.5011
λ_α	0.0226	0.0021	0.0000	0.0243	0.0016	0.0000	0.0244	0.0022	0.0000
θ_β	0.9752	0.9772	0.9771	1.0244	1.0128	1.0226	1.0252	1.0234	1.0254
λ_β	0.1169	0.1163	0.1331	0.1336	0.1477	0.1315	0.1379	0.1378	0.1357

Notes: This table presents the simulation results from three evaluation models: the non-learning model, the partial learning model and the general learning model. The posterior mean of the variables, i.e. the in-family variability, δ_α, the family level annualised mean performance, θ_α, and the cross-sectional averaged annualised alpha, are reported. We control the prior belief on the scaled parameter of the cross-sectional variability in α, ξ_α and priors on θ_α to be three distinct distributions, i.e. a diffuse prior has $log(\xi_\alpha) \sim N(-1,1)$; the low scepticism has $log(\xi_\alpha) \sim N(-5,1)$; the high scepticism has $log(\xi_\alpha) \sim N(-10,1)$. θ_α, θ_β and the scaled parameter of θ_β is assumed to have diffuse prior distribution. Panels A, B and C report the simulation results from the CAPM, 3-factor model and 4-factor model. The posterior distributions are generated by applying the MCMC method on monthly returns from 220 UK unit trusts (47 fund families).

We find a similar decreasing pattern in λ_α with the increasing level of scepticism in the prior beliefs. Such a pattern is also robust throughout different baseline evaluation models. However, the in-family variation on β seems to increase with the prior belief, e.g. λ_β of CAPM equals to 0.117 under the diffuse prior and it increases to 0.692 given the high scepticism prior. A possible reason is that the prior beliefs we apply are far below the real in-family variance of the market beta, which makes the MCMC simulation hard to converge. Because of the power in place of the extreme priors, most of the posterior β shrinks towards the prior mean, leaving several outliers which enlarge the posterior in-family variance. However, the posterior correlations between each pair of the pricing factors in Table 4.7 are too low to affect the convergence of other pricing factors.

The averaged alpha and beta both experience a decrease with the increasing level of scepticism on a larger scale than those reported in Table 4.5, for the reason that prior information is included on both the family mean and the in-family variation. For instance, alpha equals to 0.495% in Panel C of Table 4.5 given a high scepticism prior, while it is 0.366% when prior belief on θ_α is included. This finding is robust in all the types of baseline evaluation models we consider. Our simulation in Table 4.6 validates that performance evaluation of individual funds can be affected by including information on the prior view of the mean performance from the family as a whole, as well as the variation of performance among funds within the fund family. Given the situation that the sets of prior beliefs on the pricing factors do provide additional information regarding the population of returns for a particular fund family, i.e. risk shifting in different market condition, adjustment in investment strategy when facing new information or engaging in tournament among fund managers within the family, the general learning model can incorporate this information so as to provide a more precise evaluation result.

However, we find no strong evidence to support the presence of cross-factor learning in the general learning model during the simulation. The averaged posterior correlations between alphas and market betas under the three sets of prior beliefs are reported in Table 4.7. The posterior correlation, $\rho_{\theta_\alpha,\theta_\beta}$ remains at a very low level at all times, indicating that the prior information of other pricing factors has no substantial impact on the changes of the posterior family mean performance. But such a low correlation does not affect the outcome of learning, since as mentioned previously, the posterior mean of λ_k is conditional on the covariance matrix, which includes the prior information on the in-family variation and family mean value of all pricing factors. Therefore, if correlation among the mean value of different pricing factors can be omitted, the prior information can be applied to family mean value directly, which can significantly speed up the convergence of the Markov chain, but bears the loss of the co-movements of the pricing factors. On the other hand, we place no informative prior on the correlation matrix in the simulation, i.e. an inverse Wishart distribution, $\mathcal{W}^{-1}(K+1, I_{K\times K})$, is applied on the correlation matrix to represent a uniform prior on the correlation. It would certainly be possible to include an informative prior on the correlation matrix to address the dependence issue of the pricing factors if necessary. However, such a setting might involve denoting specific correlation among different market portfolios, which is beyond the scope of this research.

Table 4.6 Simulation of learning on all pricing factors

	CAPM			3-factor model			4-factor model		
λ_k prior	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
					General learning model				
$\alpha(\%)$	0.8447	0.7263	0.3664	0.9126	0.8147	0.4917	0.9669	0.8589	0.6271
β	0.9769	0.9735	0.7357	1.0249	1.0163	0.9329	1.0247	1.0164	0.9633
$\theta_\alpha(\%)$	0.7043	0.5111	0.0000	0.6709	0.4122	0.0000	0.7631	0.3743	0.0000
λ_α	0.0232	0.0023	0.0013	0.0238	0.0021	0.0011	0.0243	0.0021	0.0007
θ_β	0.9757	0.7570	0.0000	1.0243	0.7059	0.0000	1.0252	0.7449	0.0000
λ_β	0.1174	0.3211	0.6919	0.1344	0.3913	0.8738	0.1377	0.3631	0.9021

Notes: This table presents the simulation results from the general learning model. The posterior mean of the variables, i.e. the cross-sectional annualised averaged alpha, the cross-sectional averaged β, the annualised mean performance of alpha (θ_α), the mean performance of $\beta(\theta_\beta)$ and the in-family variability (λ_α) are reported. We control the prior belief on the scaled parameters of the cross-sectional variability in factor loadings, ξ_k. The prior beliefs on the mean value of the k^{th} pricing factor, θ_k, are centred at zero with a diffuse variance. The scaled parameter of θ_β is also assumed to have a diffuse prior. Panels A, B and C report the simulation results from the CAPM, the 3-factor and the 4-factor models. The posterior distributions of the variables considered are simulated by the MCMC technique by using monthly returns from 220 UK unit trusts.

Table 4.7 Posterior correlation coefficients

	CAPM			3-factor model			4-factor model		
Panel A λ_α prior	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
$\rho_{\theta_\alpha,\theta_\beta}$	-0.0253	-0.0453	-0.0046	0.0184	0.0300	0.0068	0.0253	0.0411	0.0114
Panel B Prior beliefs	Diffuse	Low	High	Diffuse	Low	High	Diffuse	Low	High
$\rho_{\theta_\alpha,\theta_\beta}$	-0.0252	0.0111	0.0647	0.0182	0.0781	0.0382	0.0249	0.0891	0.2010

Notes: This table presents the simulation results from three evaluation models: the non-learning model, the partial learning model and the general learning model. The posterior mean of the variables, i.e. the in-family variability δ_α, the family level mean performance θ_α, and the fund's individual risk level σ_R, are reported. We control the prior belief on the scaled parameter of the cross-sectional variability in α, ξ_α to be three distinct distributions, i.e. $log(\xi_\alpha) \sim N(-1,1)$, $log(\xi_\alpha) \sim N(-5,1)$ and $log(\xi_\alpha) \sim N(-10,1)$. The prior belief on the mean value of the k^{th} pricing factor, θ_k, is centred at zero with a diffuse variance. The scaled parameter of β is also assumed to have a diffuse distribution. Panels A, B and C report the simulation results from the CAPM, Fama French 3-factor model and the 4-factor model. The posterior distributions of the variables considered are simulated by the MCMC technique by using monthly returns from 220 UK unit trusts.

4.5 Conclusions

In this research, we devote our attention to analysis of how returns from other parallel funds affect the alpha of particular funds within the same fund family. We consider a general learning model in a Bayesian framework to incorporate the additional information given by other funds in the prior beliefs. We decompose the Jensen alpha as well as the loadings of each market portfolio in the factor pricing model into the combination of a family mean value and fund's idiosyncratic variation. The family mean value represents the investors' opinion on the cross-sectional mean of both alpha and factor loadings, while the in-family variation addresses how parameters from the individual fund deviate from the family mean.

To simulate this general learning model we construct the combined Gibbs samplers with the Metropolitan Hastings algorithm by using monthly NAV from 220 UK domicile equity based unit trusts belonging to 47 fund families. We also conduct a simulation based on fake returns generated by drawing from the real dataset, to validate the learning process addressed by our evaluation. In addition, to estimate the Jensen alpha we apply the general learning model to three types of factor pricing model, i.e. the CAPM, the Fama French 3-factor and the Carhart 4-factor model. We also incorporate three sets of prior belief to simulate the possible prior information on the family mean of each pricing factor and their in-family deviation, namely, diffuse prior (no information given by the prior belief); low scepticism prior (small value of in-family deviation); high scepticism prior (high value of in-family deviation).

The fake data simulation suggests that the posterior mean of in-family variation decreases given a less dispersed prior belief, indicating that individual funds' alphas might concentrate around their family means if prior information implies a serious lack of skilful managers. Moreover, the fake data simulation also suggests that the general learning model is more sensitive to the chosen prior belief, compared to the non-learning and the partial learning model discussed by JS. This is because the posterior mean of in-family variance is conditional on the covariance of different pricing factors. The general learning model can provide a compromise of performance evaluation between the actual returns delivered by the fund and the additional information on how other funds behave in the same fund family. Since the general learning model provides a full Bayesian treatment on each of the pricing factors, it is more likely to gain benefits from this cross-sectional learning.

The simulation on the real fund returns draws the same results about the posterior shrinkage in individual fund alphas within the same family as does the simulation on the fake data. In addition, we find that averaged annual cross-sectional alpha exceeds the family mean alpha under all the chosen prior beliefs. This implies that the idiosyncratic risk of individual funds provides a positive contribution to their overall performance. Since we keep only one representative fund for each share class within the fund family, the positive residual can therefore be seen as the benefits from idiosyncratic investment strategies, which are often decided by fund managers.

The contribution of this research is to provide an evaluation method of individual funds by incorporating return information given by other funds within the same fund family. Because of the full Bayesian treatment on all the pricing factors, the general learning model addresses the process of investors' rational updating in performance evaluation. In general, our empirical results suggest that the returns of peer funds within the same family have significant impact on the investors' opinion of fund's alpha. Compared with the previous method, the higher level of shrinkage from our model can better present the idea of learning across funds.

Furthermore, from the empirical Bayes perspective, if the prior beliefs are elicited by using the historical cross-sectional information, the general learning model is likely to provide more accurate evaluation results when facing the situation that fund families might engage in different family strategies to improve the performance. Since most of the family strategies would involve allocating more capital to certain funds or encouraging fund managers to compete with each other, which may lead to an increase of the cross-sectional variability among alphas, the prior beliefs can be used to simulate these strategies or to capture the pattern of in-family risk shifting during managers' tournament implied by the historical data.

Consequently, the above additional information can be included in the evaluation process to better utilise the historical fund returns provided by all the funds within the same fund family. Finally, the general learning model provides a baseline model to distinguish managers' skill from family contribution. Non-equal weight can be applied to both Θ and Λ to address the inequality in skill, and the zero-mean assumption in Λ can also be relaxed to indicate a specific drift of managers' ability.

CHAPTER FIVE

CONCLUSIONS

5.1 Research overview and implications

5.1.1 Managers' turnover

In Chapter 2, we analyse the interplay between fund performance, managerial replacement and portfolio characteristics using the data from the UK fund industry. We deploy a bootstrapping simulation to separate the managers whose performance is driven by sample variation ('luck') from those with genuine stock selection skills in order to further test the efficacy of the governance mechanism in the UK fund industry. Our results suggest that managers' replacement can be predicted by their underperformance. We also show that managers with sample-variation-driven performance are more likely to be dismissed by the fund companies than are 'unlucky' managers whose inferior performance is generated by 'bad luck'. Thus, the internal monitoring system is effective to identify managers with 'fake' skill. Conversely however, the probability of replacing those managers with genuinely poor skills is quite low, which indicates that additional factors, e.g. fund flows, might have more weights in fund companies' decision on managerial replacement. While it is found that the fund management companies are capable of identifying the skilful managers, their tolerance of managers' poor skill significantly increases the external monitoring costs to the fund investors.

5.1.2 Risk taking in fund family tournament

In Chapter 3, we analyse the risk taking behaviour in the family tournaments, and the performance consequences thereof. Our empirical investigation documents that the half-year winning funds in the family are more likely to take more risks than their peers in the same family. In terms of the risk characteristics, our results show that the winning funds tend to increase their systematic risk in the second half of the year, indicating the winners' temptation to retain their positions by holding high value and index-linked equities to mimic the market. In the analysis of performance consequences, we find that maintaining a low level of risk shifting drives the winners to outperform the losers. This result persists among various benchmarks, i.e. the observed returns, and the alphas obtained from estimating the CAPM, 3 factor and 4 factor models. However, after taking more risk funds in the winning group also show significantly higher alphas than the losing funds. In general, our results are supportive of the findings in previous studies that better performance comes with more stable levels of risk, but the research highlights that risk taking may not necessarily be an indication of inferior performance. Instead, it can be regarded as reflecting the managers' intention to win the tournament. From the fund family perspective our findings show that fund families may sacrifice the profits of certain members to benefit the others, as our results document a positive connection between cross-sectional variability of fund performance and aggregate changes in fund ranks within the family.

Our findings in Chapter 3 provide empirical evidence to support the essential role played by the fund family in fund operation. We find that fund managers value the importance of family rankings more highly than their relative performance in the segment, in order to obtain benefits from the family. Also, our results suggest that risk-adjusted returns could be the major criterion by which the fund family judges managers' skill. Since the previous literature gives little attention to the alpha-based compensation scheme, our findings shape the understanding of the motivation behind managers' risk taking and provide additional insights into the managerial incentives to engage in family tournament. From the investors' perspective, although we generally agree with previous findings in which a higher risk level leads to lower returns, our results still indicate that increasing risk exposure can be regarded as indicating managers' intention towards active trading. Thus, a more comprehensive evaluation process is necessary to incorporate this eventuality.

5.1.3 Bayesian learning and fund performance

In Chapter 4 we devote our attention to analysing how returns from parallel funds affect the alphas of particular funds within the same fund family. To achieve this objective, we propose a general learning model in a Bayesian framework to incorporate the additional information on prior beliefs. We decompose the individual fund alphas as well as the factor loadings of each market portfolio into the combination of a family mean value, which represents the cross-sectional mean, and the idiosyncratic disturbance, which addresses how parameters of individual funds deviate from the family mean. To simulate the model we construct a combined Gibbs sampler and the Metropolitan Hastings sampler with the acceptance rate no less than 44%.

The simulation results suggest that our method better addresses the learning process. The posterior variance of alpha decreases dramatically with less dispersed prior beliefs, indicating that investors' updating on fund alpha is more likely to be influenced by the performance of peer funds in the same fund family. Since the general learning model provides a full Bayesian treatment of each of the factor loadings as well as the Jensen alpha, it is more likely to gain benefits from this cross-sectional learning. We also find that the averaged cross-sectional alpha exceeds the family mean alpha under all the chosen prior beliefs. This implies that the idiosyncratic risk of individual funds provides a positive contribution to their overall performance.

Chapter 4 provides an evaluation method of individual funds by incorporating returns information given by other funds within the same fund family. The method offers an approach to adjust the estimation of fund alphas by investors' arbitrary beliefs on the overall skill level of the fund family. If the prior beliefs elicited refer to the historical evidence of family strategies, i.e. shifting performance within the family or reallocating resources to certain funds, the method is likely to provide more accurate results. Moreover, from an empirical Bayes perspective, our method can be used as the baseline model to conduct a recursive analysis which updates prior beliefs by using the newly simulated posterior beliefs to better capture the randomness of fund alpha. Finally, by allowing specific prior belief to be placed on each of the pricing factors, our method can improve our understanding of the implementation of trading strategies adopted by both individual funds and the fund family.

This research provides a comprehensive analysis on both the performance shifting and the evaluation technique in the context of the UK fund industry. The two empirical chapters, Chapter 2 and 3, discuss the major factors that have substantial impact on funds' performance. In Chapter 3, our results suggest that the underperforming managers are less likely to increase their overall risk exposure more than the overperforming ones due to increasing uncertainty of the future performance and their anxious career concern. This is therefore consistent with the findings discussed in Chapter 2 where fund companies are found to be capable of identifying and replacing non-skilful managers, particularly when the superior performance is achieved by sample variation. Meanwhile, the performance consequence suggests that taking extra risk brings no benefits to the underperformers, which even increases the chance of being replaced by the fund companies.

In addition, the family tournament phenomenon documented in Chapter 3 implies a potential interplay among fund managers within the same fund family. The fund companies also undertake various family strategies to improve the performance of a certain fund, which further emphasizes the crucial role played by the fund families. Therefore, the evaluation method proposed by Chapter 4 extends the conventional method by incorporating additional information provided by the peer funds as well as the fund family to offer more precious evaluation results. Hence, our simulation results in Chapter 4 further validate the conjecture of the cross-fund learning in the fund performance evaluation.

5.2 Limitations and future research

This research makes a critical contribution to a better understanding of fund managers' turnover, fund family tournament and investors' Bayesian learning by way of a case study of the UK unit trust funds. Despite the new insights it sheds on fund performance and its evaluation, several limitations do exists, which call for further research in the future.

First, the Bayesian learning model we propose in Chapter 4 can be extended by incorporating additional explanatory variables. We assume in the current study that the mean performance and the idiosyncratic performance contribute equally to the evaluation. However, to be more accurate, specific weights as well as prior information should be designed at the family-level modelling to better address the learning process.

Second, although it is beyond the scope of this research to provide specific information on the prior beliefs of the correlation matrix, it is nevertheless worth noting that it could obtain important insights by further analysing the co-movements among different factors in the pricing model. Bayesian estimation can be applied further to provide an approach to extend understanding of the rational learning in the field of asset pricing.

Finally, despite the popularity of using observed returns to estimate fund volatility, the returns of the holding equities from the fund can also be considered as an alternative to the description of fund managers' instant strategy switching.

However, no existing data provider offers access to high frequency datasets on detailed fund holdings. With improved data availability, high frequency data analysis could prove to be a very fruitful research area in the future.

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